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Content

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MEASURING REGIONAL SUSTAINABILITY IN THE EU: DEVELOPING AND APPLYING ADJUSTED HDI VARIANTS WITH FUNCTIONAL DATA ANALYSIS

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Abstract

Addressing the gap in regional sustainability monitoring in the EU, this study assesses the applicability of composite sustainability indicator families at the NUTS 2 level and develops a methodology for regional variants of the Human Development Index (HDI) family. Nine indicator families were systematically assessed against four applicability criteria: communicability, relationship to GDP, sustainability dimension coverage, and territorial applicability. The HDI family emerged as the only methodologically sound basis for the NUTS 2 sustainability assessments. Four regional indices (R-HDI, R-IHDI, R-GDI, and the planetary pressures-adjusted R-PHDI) were derived from Eurostat and EDGAR data and piloted on 84 NUTS 2 regions across six Central European countries (V4, Germany, Austria) for 2000–2024. Functional data analysis with global envelope tests confirmed that conclusions about convergence depend on indicator choice: statistically significant V4 vs DE+AT differences under R-HDI ($p = 0{,}001$) disappeared following environmental adjustment via R-PHDI ($p = 0{,}487$), with emission-intensive regions substantially penalised. The R-IHDI and R-GDI are exploratory variants that required methodological compromises owing to the absence of regional-level data at the NUTS 2 level. This study presents a novel derivation and empirical application of a combination of regional HDI-type variants, environmental adjustment, and functional data analysis at EU NUTS 2 level.

Keywords: sustainability indicators; NUTS regions; functional data analysis; cohesion policy; regional human development

JEL Classification: C14, Q01, R11, R58

1. Introduction

1.1. Research background

Human civilisation has entered the Anthropocene, a geological epoch defined by the dominant influence of human activity on planetary systems (Crutzen, Stoermer, 2000), manifesting as a global polycrisis encompassing climate change, global security disruption, energy instability, and deepening social inequalities (Lawrence et al., 2024). This situation poses a fundamental challenge to the concept of sustainable development (WCED, 1987), which has become the generally accepted framework for addressing global development and environmental threats. However, an effective response depends directly on the ability to adequately measure and monitor the impact of the polycrisis. The need for systematic monitoring first emerged in 1992 in Rio de Janeiro (United Nations, 1992) and gradually intensified through summits in Johannesburg (2002) up to Rio+20 (2012), where the call to move beyond GDP as the primary measure of development was articulated for the first time at the global level (United Nations, 2002; United Nations, 2012). This line of commitments culminated in the adoption of the 2030 Agenda and its 17 Sustainable Development Goals, the monitoring of which is based on a system of global indicators (United Nations, 2015).

While sustainability monitoring under the 2030 Agenda is gradually becoming established at the global and national levels, its translation to the regional level remains a substantial methodological challenge. Within the EU, regional statistics cover a range of demographic, social, and environmental indicators alongside GDP (Eurostat, 2026b); however, no unified synthetic sustainability framework exists at this level. GDP fails to capture environmental degradation, unpaid work, income distribution, or the social costs of economic activity (Stiglitz, Sen, Fitoussi, 2009). Moreover, national-level monitoring obscures substantial subnational disparities, rendering disaggregated regional assessments indispensable. Yet, it is precisely at the regional level, where development strategies are implemented, that multidimensional assessments encounter persistent barriers of data gaps and methodological inconsistencies.

The scope and heterogeneity of existing sustainability indicators reflect the complexity of the concept itself, which encompasses economic, social, environmental, and sometimes institutional dimensions of sustainability. Indicators have emerged in diverse contexts, responding to varying political impulses and drawing on contrasting theoretical positions and economic models, from the neoclassical emphasis on green growth and decoupling, through ecological economics, to post-growth approaches (Goossens et al., 2007; Liu et al., 2024). The result is a confusing spectrum ranging from extensive indicator sets, such as the 231 indicators of the 2030 Agenda (United Nations, 2015), to synthetic composite indices that are difficult to translate to the regional level, with more demanding data requirements.

Composite indices, which aggregate multiple dimensions into a single comprehensible value, represent the most promising direction for regional analysis, meeting the need for accessible communication on the state of sustainable development to policymakers and the general public. In this context, several significant families of indicators[1] can be identified, such as the SDG Index, Ecological Footprint (EF), or welfare-adjusted indicators such as the GPI/ISEW. Recently, the family of human development indices (HDI) has gained particular significance. Since 1990, the UNDP has demonstrated that the HDI can effectively aggregate key dimensions of development, while its expanded variants – the Inequality-adjusted Human Development Index (IHDI) (since 2010), Gender-related Development Index (GDI) (since 2014), and Planetary pressures-adjusted Human Development Index (PHDI) (since 2020) – offer unique potential for comprehensive assessment (UNDP, 2024), including at the regional level (Hardeman, Dijkstra, 2014).

Sustainable development is a stated objective of the European Union, anchored in primary law since the Treaty of Amsterdam (European Union, 1997) and reaffirmed in the Treaty of Lisbon (European Union, 2007). The European Sustainable Development Strategy (European Commission, 2001) and subsequent documents have gradually integrated environmental, social, and economic dimensions into the EU's strategic planning. The European Green Deal (European Commission, 2019) operationalised this commitment through green growth and the decoupling of economic performance from environmental pressure, in line with the Paris Agreement, while simultaneously raising demands for monitoring environmental and social impacts at the level of individual regions.

In practice, the EU's sustainability strategy is implemented primarily through cohesion policy, which is the main investment instrument for reducing regional disparities. The analytical framework for regional assessment is provided by the Nomenclature of Territorial Units for Statistics (NUTS) classification, whose NUTS 2 level has been used for regional statistics since the 1970s and was formally codified as the basic level for defining regions eligible for support under cohesion policy by a regulation in 2003 (European Union, 2003; Eurostat, 2026a). A key

[1] The term *'family of sustainability indicators'* is used throughout this paper as a working label for a group of indicators sharing common characteristics, a conceptual basis, a methodological approach, or a relationship to GDP, and does not claim to constitute a general definition.

methodological tension arises from the fact that while the EU's strategic objectives are becoming multidimensional, the main allocation mechanism remains linked to regional GDP per capita. Therefore, the NUTS 2 level is a natural framework for assessing indicators capable of simultaneously capturing the social, environmental, and economic dimensions of development.

1.2. Research gap, objectives and questions

There is a significant mismatch between the growing demand for sustainability monitoring at the regional level and the availability of suitable analytical tools. None of the main families of indicators has been comprehensively assessed in terms of their applicability at the NUTS 2 level, while considering data availability, methodological consistency, and coverage of all dimensions of sustainability. The aim of this study is therefore to assess the applicability of composite sustainability indicator families for regional sustainability monitoring and to derive a methodology for applying adjusted variants of the HDI family (R-HDI, R-IHDI, R-GDI, R-PHDI) for use at the regional level (NUTS 2), with their analytical potential demonstrated through a pilot application using functional data analysis.

A precondition for this aim is the availability of suitable regional data. Eurostat systematically collects regional data for the NUTS 2 level, which provides the basis for constructing composite indicators (Eurostat, 2026b). complemented by greenhouse gas emissions from the EDGAR database(Crippa et al., 2024). Assessing the extent to which these sources permit the construction of the adjusted HDI variants at the NUTS 2 level is itself part of the research task.

The research questions were formulated to reflect the logical progression of the research: from the identification of suitable indicators (RQ1), through the assessment of the dataset (RQ2) and the derivation of a regional methodology (RQ3), to empirical verification (RQ4). Each is assigned a testable hypothesis of an analytical (H1 and H2) or empirical nature (H3 and H4).

- **RQ1**: Which families of composite sustainability indicators are most suitable for assessing regional development at the NUTS 2 level in terms of sustainability dimension coverage, methodological consistency, and data availability?

  H1: *In terms of coverage of sustainability dimensions, methodological consistency, and data availability at the NUTS 2 level, the HDI family represents the most suitable basis for regional sustainability assessment in the EU.*

- **RQ2:** What is the availability of data in the Eurostat and EDGAR databases for the construction of selected indicators at the NUTS 2 level for the period 2000–2024, what are their limitations, what methods can be used to address the identified data gaps, and what is the impact of changes to the NUTS classification on the consistency of time series?

  H2: *Data availability in the Eurostat and EDGAR databases is sufficient for constructing the R-HDI and R-PHDI at the NUTS 2 level for the period under review; however, for the R-IHDI and R-GDI, methodological compromises are required in the form of substitutions or approximations of certain sub-indicators.*

- **RQ3**: How can a regional methodology for adjusted HDI variants (R-HDI, R-IHDI, R-GDI, and R-PHDI) be derived from the available Eurostat and EDGAR data, including the identification of necessary methodological compromises and possible substitutes for unavailable sub-indicators?

  H3*: Adjusted variants of the HDI (R-IHDI, R-GDI, R-PHDI) at the NUTS 2 level exhibit different regional patterns than the standard R-HDI, with the R-PHDI identifying regions with high emission intensity as particularly problematic.*

- **RQ4**: What trajectories and statistically significant differences in regional development does functional data analysis using global envelope tests identify in the time series of regional indicators for a selected group of countries (V4, Germany, and Austria) over the period 2000–2024?

  H4: *Trajectories of regional development measured by adjusted variants of the HDI differ statistically significantly between the V4 countries and DE+AT countries, with the nature of these differences depending on the index variant used.*

This article proceeds from a theoretical overview of sustainability indicator families (Chapter 2), through the methodology and data (Chapter 3), to a pilot application and its discussion (Chapters 4–5), before concluding (Chapter 6).

2. Theoretical Background of Sustainability Indicators

2.1. The Development of Concepts and Measures of Development: From Prosperity to Sustainability

Early attempts to measure human societal development focused primarily on prosperity and the creation of national wealth. Kuznets's system of national accounts (Kuznets, 1934) established GDP as the dominant measure of national wealth, although the author himself warned that a nation's wellbeing is difficult to derive from it. After the Second World War, GDP entrenched itself as a politically powerful indicator of prosperity (Lepenies, 2016). However, this model of economic growth encountered specific environmental and social failures. Growth-driven industrialisation brought chemical contamination (Carson, 1962), while the oil crises of 1973 and 1979 signalled resource limits (Meadows et al., 1972). Georgescu-Roegen (1971) demonstrated that the irreversible degradation of natural capital is a thermodynamically inevitable consequence of economic growth. From a social perspective, mass poverty persisted and income inequality deepened (Stiglitz, Sen, Fitoussi, 2009; Piketty, 2013).

The convergence of environmental and social failures led to efforts to find a global solution. The UN Conference in Stockholm (1972) placed environmental issues on the international political agenda for the first time and resulted in the establishment of the UNEP (United Nations, 1972). A breakthrough came with the report *Our Common Future* (WCED, 1987), which defined sustainable development as development that meets the needs of the present without compromising the ability of future generations to meet their own needs. The report also defined three interlinked pillars — economic, social, and environmental — the simultaneous fulfilment of which has become a normative requirement for any sustainability indicator. Some authors advocate the addition of a fourth institutional pillar as a prerequisite for the functioning of the remaining three dimensions (Spangenberg, 2002). However, agreement on the need for a global solution has not translated into a consensus on approaches and methods of monitoring, as different economic models and theoretical positions imply different conceptions of what to measure.

The key distinction lies in the relationship to natural capital. At one end stands the classical growth model, which ignores externalities and treats natural capital as an unlimited input for production (Solow, 1956). Weak sustainability assumes substitutability (Hartwick, 1977), whereby technological progress and capital accumulation can compensate for natural capital loss. Medium sustainability acknowledges the existence of critical natural capital that cannot be replaced (Pearce, Turner, 1990). Strong sustainability argues that natural capital comprises critical and irreplaceable components — a stable climate, biodiversity, and biogeochemical cycles — whose loss is irreversible and, therefore, require absolute preservation (Daly, 1990). The scientific operationalisation of this requirement is the concept of planetary boundaries, identifying nine Earth system processes whose exceeding threatens the stability of the Holocene climate (Steffen et al., 2015). At the other end of the spectrum stands the Gaia concept (Lovelock, 1979), which views humanity not as the owner of nature but as part of it.

The environmental and social failures of industrialisation (pollution, climate change, and deepening inequalities) are, from an economic perspective, externalities caused by market failure. The Pigou tradition (Pigou, 1920) proposes solutions through taxes and subsidies, whereas Coase's theorem (1960) proposes solutions through negotiation and the allocation of property rights. Both traditions assume that externalities can be identified, quantified, and internalised. However, many environmental and social externalities are global, cumulative, and irreversible, which goes beyond classical internalisation mechanisms (Stern, 2006). The key paradox lies in the fact that GDP not only fails to capture externalities but sometimes actively counts them as economic benefits: the costs of cleaning up an environmental disaster or expenditure on healthcare caused by pollution increase GDP, even though they represent social losses (Daly, Cobb, 1989; Costanza et al., 2012).

Different responses to the issues of externalities and capital substitutability have led to different economic paradigms and sustainability monitoring tools. Costanza et al. (2012) identified three basic scenarios: the current economic model assuming full capital substitutability and economic growth measured by GDP; green growth utilising decoupling (European Commission, 2019) and incorporating environmental adjustments in the form of green GDP or genuine savings; and ecological economics (Daly, 1996), which requires indicators of the absolute state of natural capital, such as the ecological footprint encompassing also post-growth and degrowth perspectives (D'Alisa, Demaria, Kallis, 2015; Kallis, 2011) favouring wellbeing indices independent of economic performance. Doughnut economics (Raworth, 2017) synthesises the social foundation and ecological ceiling.

The spectrum of beyond-growth approaches is reflected at the institutional level in the EU in the Beyond GDP initiative (European Commission, 2007; Wesselink et al., 2007; European Parliament, 2023). This spectrum is complemented by eco-socialist approaches that locate the systemic causes of the polycrisis in the logic of capitalist accumulation, including both productivist variants linking the Marxist theory of the metabolic rift to the ecological crisis and non-growth and post-growth eco-socialist positions (Löwy, 2005; Hickel, Kallis, 2020).

Over the past two decades, the recognition that development is a multidimensional phenomenon that cannot be adequately captured by a single aggregate (Stiglitz, Sen, Fitoussi, 2009) has intensified the tension between multidimensionality and the communicative power of single-figure measures. GDP dominates precisely because no dashboard or set of indicators can fully replace its simplicity (Lepenies, 2016). The response is the development of composite indices that aggregate multiple dimensions into a single value while maintaining interpretability, as demonstrated by Jansen et al. (2024) and the associated WISE database, which compiles 244 beyond-GDP metrics organised according to the dimensions of wellbeing, inclusion and sustainability (Liu et al., 2024). The result is a landscape of indicator families, each covering a different cross-section of dimensions and based on a different economic paradigm.

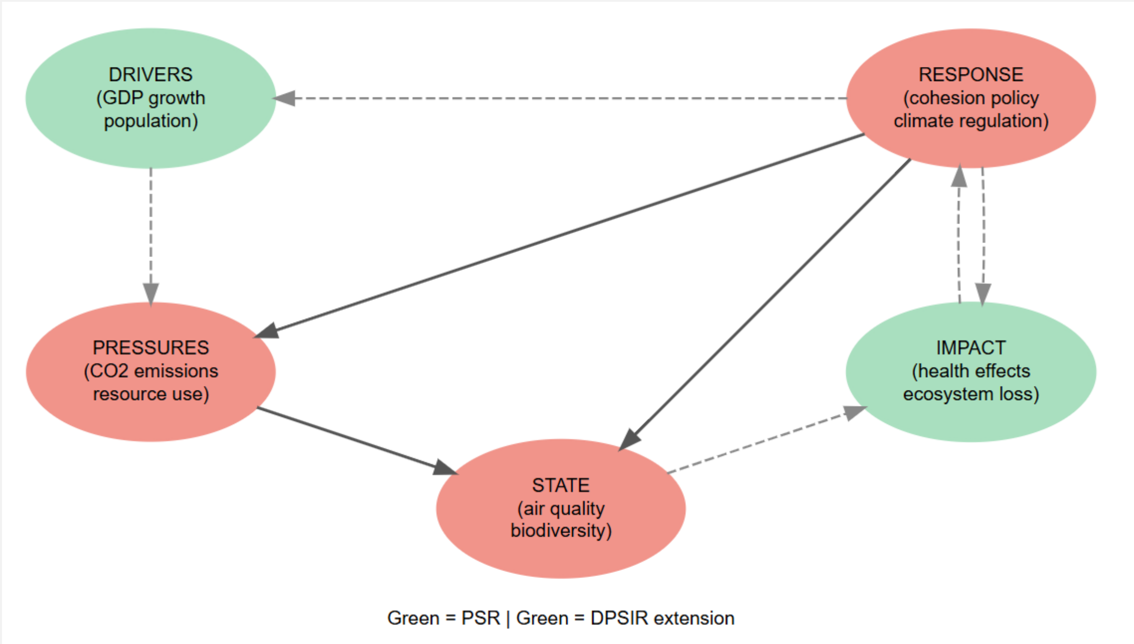
One's position on this spectrum of theoretical and paradigmatic approaches has direct methodological implications for measuring sustainable development. The choice of an indicator is never purely technical, but always also a value-based choice, reflecting implicit assumptions about the relationship between humans and natural capital, distributive justice, and the limits of economic growth.

2.2. Approaches to the Classification of Sustainability Indicators

This extensive and methodologically diverse set of indicators and approaches reflects the fact that sustainability is not a clearly defined phenomenon, but a normative concept encompassing economic, social, and environmental dimensions, whose interrelationships and priorities are the subject of both scientific and political debate (Moldan, Janoušková, Hák, 2012). The various institutional and scientific contexts in which the indicators were developed have led to different classification approaches, an overview of which is an essential prerequisite for a reasoned selection of tools suitable for regional sustainability analysis in the EU.

The first systematic attempts to classify sustainability indicators were based on the need to structure the growing volume of environmental data into a logically coherent whole. The methodological approach was developed by the OECD (1993) as the pressure-state-response (PSR) causal framework, in which human activities generate pressures on the environment, to which society responds with policy measures. This approach made it possible to systematically link indicators into a system of causes-and-effects. The European Environment Agency extended this framework to the Drivers–Pressure–State–Impact–Response (DPSIR) framework by adding driving forces and impacts on human health and ecosystems (Smeets, Weterings, 1999) (Figure 1). However, both frameworks primarily cover the environmental dimension; they do not systematically capture social development and economic wellbeing, nor do they allow for aggregation into a single comparable value.

Figure 1: The PSR and DPSIR Frameworks for Sustainability Indicator Classification

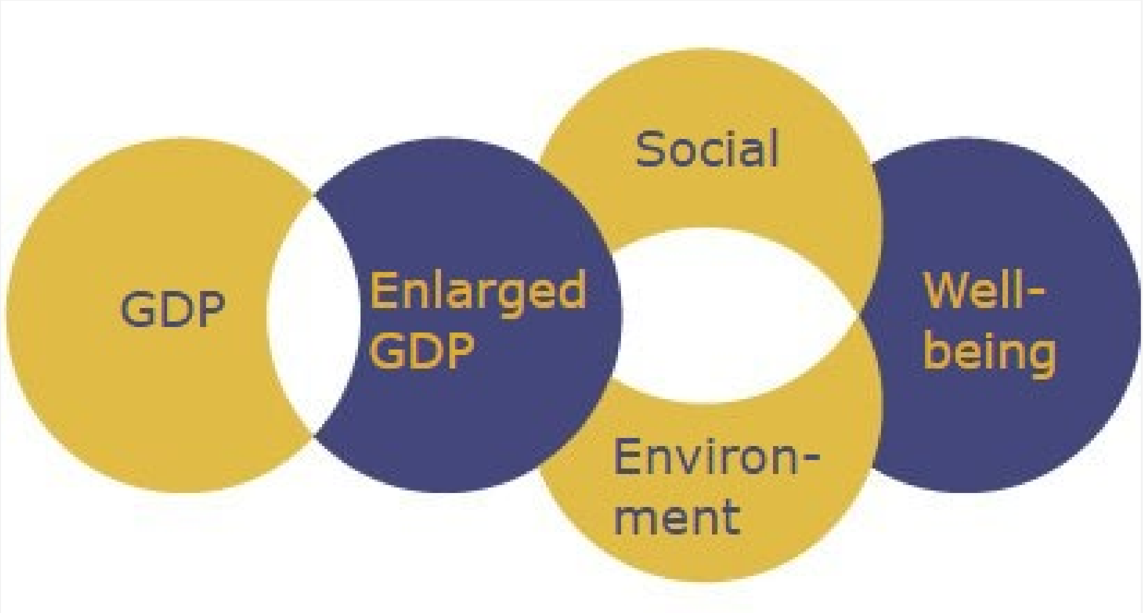


Source: Authors' own elaboration based on OECD (1993) and Smeets and Weterings (1999).

Note: Red nodes (Pressure, State, Response) and solid arrows represent the original PSR framework (OECD, 1993); green nodes (Drivers, Impact) and dashed arrows represent the DPSIR extensions (Smeets, Weterings, 1999).

At the institutional level, the first reviews of alternative indicators primarily responded to the dominance of GDP in political decision-making. Goossens et al. (2007) classify indicators according to their relationship to GDP into four groups: i) indicators that include or adjust for GDP, ii) indicators that complement GDP, iii) indicators independent of GDP, and iv) indicator sets. The parallel framework of the European Commission's Beyond GDP initiative (2007) adds a thematic dimension, ranging from the extension of GDP through social and environmental indicators to indicators of wellbeing, and visually depicts their intersections beyond the scope of economic performance (Figure 2). This institutional interest is further evidenced by the European Parliament's study *Beyond Growth: Pathways towards Sustainable Prosperity in the EU* (European Parliament, 2023). Both approaches use GDP as a reference point; alternative indicators serve as a complement or correction, not a substitute.

Figure 2: The 'Beyond GDP' Classification of Progress Indicators



Source: European Commission (2007).

Two studies provided a major methodological impetus by approaching the classification of indicators from the perspective of scientific validity. Böhringer and Jochem (2007) subjected 11 sustainability indices to critical analysis and concluded that most of them do not meet the basic scientific requirements of validity and consistency. Munda (2005) identified a fundamental problem with aggregation: sustainability is a multi-criteria problem in which standard averaging methods implicitly assume the substitutability of dimensions. He therefore proposes a non-compensatory approach, which does not allow a high value in one dimension to compensate for a low value in another, noting that this choice is not technical but normative. The theoretical basis is provided by Neumayer (2013), whose classification along a scale from weak to strong sustainability has become the standard reference framework for the paradigmatic classification of indicators. The OECD and JRC responded to this criticism by publishing a handbook on composite indicator construction (Nardo et al., 2008), which serves as a methodological reference standard for composite sustainability indices.

Bell and Morse (2008) contribute a fundamental epistemological insight into this methodological debate: every indicator is a construct reflecting the value assumptions and paradigmatic position of its creators, not a neutral representation of reality. The paradox of GDP lies in its capacity to conceal its constructed nature behind the appearance of an objective and universal measure (Lepenies, 2016), thereby establishing itself as a normative standard against which all alternatives are assessed as mere supplements or corrections. This epistemological caveat applies equally to alternative sustainability indicators: their selection is never purely technical choice but always a value-based one.

2.3. Normative basis and dimensional classification of sustainability indicators

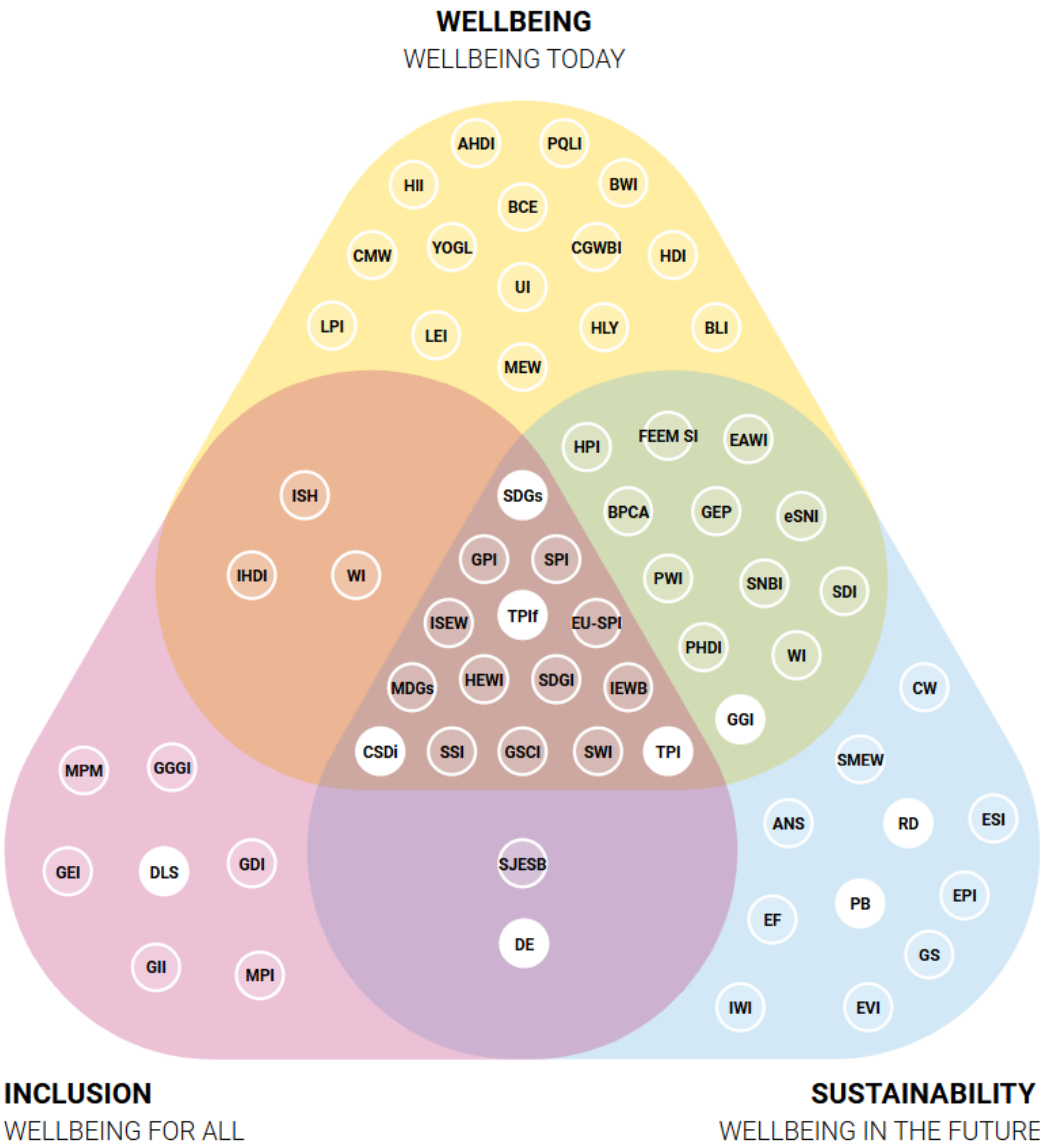
The classification approaches described above, encompassing the relationship to GDP as a reference point, coverage of sustainability dimensions, and paradigmatic position on the weak–strong sustainability spectrum, provide the basis for a systematic overview of existing sustainability indicators. The normative content of the sustainability dimensions is most widely accepted globally within the 2030 Agenda and its 17 Sustainable Development Goals (SDGs) (United Nations, 2015), which built on the Millennium Development Goals (MDGs, 2000–2015) and expanded their scope from developing countries and the basic dimensions of poverty and health to a universal framework for all countries (United Nations, 2000).

The 2030 Agenda thus reveals the ambivalent position of GDP: economic growth is explicitly included as SDG 8, but as one of 17 equal dimensions, not as an overarching aggregate. This ambivalence is not coincidental, as the SDGs had to maintain a link to the mainstream growth model in order to be politically acceptable (Hirai, 2022), even though their environmental dimension refers to elements of strong sustainability. Thus, GDP measures a legitimate but narrow slice of what the SDGs consider sustainable development and remains part of their framework as one of the dimensions, not as an overarching measure. This gradual shift in normative scope is visually captured in Figure 2.

The WISE (Wellbeing, Inclusion, Sustainability) framework provides a synthesis of modern approaches; its conceptual basis was systematically developed by Jansen et al. (2024) and empirically operationalised through a database of 244 beyond-GDP metrics by Liu et al. (2024). Unlike previous classification approaches, WISE classifies indicators not according to their relationship to GDP or the causal logic of PSR/DPSIR, but according to which aspect of human and planetary wellbeing they measure. The Wellbeing dimension captures quality of life, Inclusion captures the distribution of wellbeing across population groups, and Sustainability captures ecological limits as a necessary condition, not as a supplementary correction. A visual representation of this framework is provided by the WISE triangle (see Figure 3*)*, which maps over 60 beyond-GDP metrics according to their affiliation with the individual dimensions. The central position of the SDGs at the intersection of all three dimensions visually confirms their role as the most widely accepted normative foundation and their institutional viability.

However, the database includes only metrics designed at the national level (Liu et al., 2024) and therefore does not provide systematic data at the subnational level.

Figure 3: The WISE Triangle — Beyond-GDP Metrics by Dimension



Source: WISE Horizons Project, Beyond-GDP, 2024

Note: The three vertices represent Wellbeing Today (current quality of life), Wellbeing for All (distributional equity), and Wellbeing in the Future (intergenerational sustainability), operationalising the Brundtland definition (WCED, 1987).

Table 1 provides an overview of the classification approaches. None of them, on their own, provides a sufficient basis for selecting indicators suitable for regional sustainability analysis, owing to their environmental focus, the retention of GDP as a reference point, their orientation towards the national level, or the absence of a ready-made selection tool.

Table 1. Main Classification Approaches to Sustainability Indicators

Classification Approach	**Main sources**	**Sustainability paradigm**	**Coverage of sustainability dimensions**	**Relationship to GDP**
Causal frameworks (PSR/DPSIR): environmental monitoring tools	OECD (1993); Smeets, Weterings (1999)	W–M	Env only	Beyond GDP
GDP-oriented approaches: sustainability as a correction or extension	Goossens et al. (2007); European Commission (2007)	W–M	E + Env + Soc (partially)	GDP as an unavoidable reference point
Critical methodological approaches: scientific validity and paradigmatic assumptions	Böhringer, Jochem (2007); Munda (2005); Neumayer (2013)	M–S	All dimensions — at the methodological level	Critical — questions the neutrality of measurement and aggregation
Institutional frameworks (SDGs): universal normative references	United Nations (2015); Hirai (2022)	W–S	E + Soc + Env (+ governance in some implementations)	Part of the framework as one of the dimensions (SDG 8)
Dimensional frameworks (WISE): wellbeing as an organisational principle	Jansen et al. (2024); Liu et al. (2024)	M–VS	WB + I + Sus (including planetary boundaries as an ecological ceiling)	Goes beyond GDP

Source: Authors' own compilation based on the sources cited in the table.

Note: Sustainability paradigm: W = weak, M = medium, S = strong, and VS = very strong sustainability (Neumayer, 2013; Costanza et al., 2012). Dimension coverage: E = economic, Soc = social, Env = environmental, WB = wellbeing, I = inclusion, Sus = sustainability.

2.4. Indicator Sets vs. Composite Indices: The Case for Aggregation

Efforts to translate the concept of sustainable development into measurable practices have resulted in two methodologically distinct strategies. The first strategy involves indicator sets that emphasise comprehensiveness, thereby capturing the heterogeneity of sustainability through a larger number of sub-indicators covering the economic, social, and environmental dimensions simultaneously. The scope of these sets varies significantly, from a few dozen indicators in the case of the OECD Green Growth Indicators (OECD, 2017) to the 231 global indicators of the 2030 Agenda (United Nations, 2015). The strength of this approach lies in its comprehensiveness; no dimension is lost through aggregation, each indicator remains interpretable on its own, and the set as a whole allows progress to be tracked across the entire scope.

Visualised dashboards have emerged as a response to the complexity of extensive indicator sets; examples include the SDSN SDG dashboards (2019) and Eurostat's interactive database (Eurostat, 2025), which facilitate navigation through the data but do not resolve the underlying problem. Owing to their analytical depth and complexity, indicator sets primarily serve as tools for experts rather than policymakers and the public. Janoušková et al. (2019) show that they serve primarily to stimulate expert debate, not for high-level operational decision-making. Sébastien and Bauler (2013) distinguish between their direct *use* and indirect *influence* on policy frameworks, noting that the latter function predominates in large-scale sets. The methodological standard of Nardo et al. (2008) summarises that indicator sets are richer in information but less suitable for high-level communication than composite indices are.

The second strategy involves composite indices that address this communication deficit. By aggregating multiple dimensions into a single value, they provide a single point of reference, enabling direct comparisons between regions and tracking trends over time without the need to interpret dozens of individual indicators. Nardo et al. (2008) state that composite indicators facilitate inter-territorial benchmarking, empirically confirmed by Sébastien and Bauler (2013) in the EU context. Composite indices thus gain political influence because they offer a comprehensible benchmark for comparing performance between countries, while extensive sets of indicators tend to remain confined to expert debate. Aggregation, however, entails inevitable methodological costs, including loss of information and the need to choose weights, normalisation procedures and aggregation methods.

The choice between a composite index and an indicator set is not merely a matter of communication; it is also paradigmatic. Munda (2005) demonstrated that the choice of aggregation method is not technical but normative, as it reflects an implicit position on the weak–strong sustainability spectrum. Usubiaga-Liaño and Ekins (2024) updated this argument, stating that linear aggregation operationalises weak sustainability, while multiplicative or non-compensatory approaches meet the requirements of strong sustainability. Vintar Mally (2012) points out that many composite indices conceal this normative conditioning behind a veneer of objectivity, and the choice of a composite index therefore always requires explicit paradigmatic justification.

Despite all these methodological tensions, composite indices prevail in both political practice and academic research. The reason is a pragmatic necessity: a composite index, even with its methodological compromises, offers a better basis for communicable decision-making than a confusing set of hundreds of indicators does. Jansen et al. (2024) document that the WISE database now includes 244 beyond-GDP metrics, most of which take the form of composite indices or their components. Lepenies (2016) notes that the political power of a single-number measure is so strong that it draws alternatives towards the same form, even when their authors share methodological reservations. In this regard, Bell and Morse (2008) point out that this constructed nature of the measure, masked by an appearance of neutrality, is the same epistemological problem that originally characterised GDP. The result is a landscape of indicator families, each with a different cross-section of dimensions, paradigmatic positions, and data requirements.

2.5. Landscape of Sustainability Indicator Families

Efforts to measure sustainability have resulted in the emergence of diverse families of indicators since the 1970s in response to the shortcomings of GDP. Existing reviews either cover selected composite indices in terms of policy relevance (Pichon et al., 2021) or systematically map a broader set of indicators (Singh et al., 2012; Hák, Janoušková, Moldan, 2016; Custodio, Hadjikakou, Bryan, 2023); however, a unified comparative framework covering the entire spectrum of approaches is lacking. This overview is therefore based on the criteria of international recognition and citation, multidimensionality, or paradigmatic relevance and potential applicability for inter-territorial comparisons (Böhringer, Jochem, 2007; Nardo et al., 2008) and identifies the main families covering the entire spectrum of approaches to measuring sustainability.

By applying the three classification axes established in Chapters 2.2 and 2.3 (relationship to GDP, coverage of sustainability dimensions, and position on the weak–strong sustainability spectrum), nine main families can be identified. GDP serves as the reference point, an indicator of the economic dimension without social and environmental components, the limitations of which motivated the emergence of all other indicators. Table 2 provides an overview of the families, including their main representatives and sources.

Table 2: Overview of Sustainability Indicator Families

No.	Family	Main representatives	Dimension	Main source
-	GDP — an indicator of the economic dimension	GDP, GDP per capita	E	Beyond GDP (2007)
1	Green economy indices — extended national accounts	Green GDP, ANS/Genuine Savings, SEEA, Decoupling indicators, and IWI.	E + Env	Goossens et al. (2007); Beyond GDP (2007)
2	Footprint indices and biophysical limits	EF, CF, WF, MF, LF, Planetary Boundaries, LPI	Env	Hickel (2020), Hoekstra, Wiedmann (2014), Steffen et al. (2015); WWF (2024)
3	Environmental performance indices — policy effectiveness	ESI, EPI, CCPI	Env	Singh et al. (2012)
4	Welfare-adjusted measures — GDP adjusted for externalities	MEW, ISEW, GPI	E + Soc + Env	Daly and Cobb (1989) and Cobb et al. (1995), Goossens et al. (2007)
5	HDI family — human development and variants	HDI, IHDI, GDI, MPI, PHDI	Soc + E (+Env via PHDI)	Hickel (2020); De Neve, Sachs (2020), UNDP (2020)
6	Wellbeing indices — quality of life without GDP	HPI, GNH, BLI, SPI/EU-SPI	Soc + W + I	Custodio et al. (2023); Jansen et al. (2024), Porter, Stern and Green (2014), De Dominicis et al. (2024
7	SDG-based indices — progress towards global goals	SDG Index, SDG Dashboard	E + Soc + Env	Hák et al. (2016); De Neve, Sachs (2020)
8	Indicator sets — multidimensional monitoring	SDG Indicators, EU SDG, OECD GGI	E + Soc + Env	Hass et al. (2002); Hák et al. (2016)
9	Subjective indicators — quality of life assessment	WHR/Cantril, Gallup WP	W + I	De Neve, Sachs (2020)

Source: Authors' own compilation based on the sources cited in the table.

Note: E = economic, Soc = social, Env = environmental, W = wellbeing, I = inclusion.

2.5.1. Environmental indices

The environmental family comprises three methodologically distinct groups of indicators, united by their focus on the environmental dimension of sustainability while differing in their relationship to GDP and paradigmatic positions.

The first group consists of green economy indices based on the system of national accounts, which extend to include environmental capital. A pioneering attempt was **Green GDP,** which deducts the costs of environmental degradation from the GDP (Goossens et al., 2007). A more sophisticated operationalisation is provided by **Genuine Savings**, or Adjusted Net Savings (ANS), which measures the actual rate of savings after considering human and natural capital (World Bank, 2021). The standardised statistical framework for both variants is **the System of Environmental-Economic Accounting** (SEEA) (United Nations et al., 2014). The family is complemented by **decoupling indicators**, which measure the degree to which environmental pressure is decoupled from economic growth (OECD, 2002), and **the Inclusive Wealth Index** (IWI), which aggregates physical, human, and natural capital into a single measure of national wealth as an alternative to both GDP and the HDI (UNU-IHDP, UNEP, 2012).

The second group consists of footprint indices, which measure the pressure of human activity on ecosystems in natural biophysical units. **The Ecological Footprint** (EF) converts resource consumption and emissions into an area of biologically productive land in global hectares and compares it with the planet's available biocapacity (Wackernagel, Rees, 1996). The family of footprints has gradually expanded to include the carbon footprint (CF), water footprint (WF), material footprint (MF), and land footprint (LF) (Hoekstra, Wiedmann, 2014). A paradigmatically related approach is the concept **of planetary boundaries**, which identifies nine Earth system processes, the exceeding of which threatens the stability of the Holocene climate (Steffen et al., 2015). Trends in vertebrate populations as indicators of the state of global biodiversity are monitored by the Living Planet Index (LPI) (WWF, 2024).

The third group consists of environmental performance indices, which assess countries' performance in the field of environmental policies. These include **the Environmental Sustainability Index** (ESI), developed by Yale and Columbia University (Esty et al., 2005). Its successor is **the Environmental Performance Index** (EPI), which regularly assesses countries' progress in the areas of climate, ecosystems, and environmental health (Wendling et al., 2020). **The Climate Change Performance Index** (CCPI), produced by the consortium of Germanwatch, the NewClimate Institute, and CAN, specialises in assessing climate performance and compatibility with the Paris Agreement (Burck et al., 2024).

2.5.2. Welfare-adjusted indicators

Welfare-adjusted indicators represent the oldest category of alternative indicators to GDP, sharing the monetary adjustment of national accounts in favour of welfare. A pioneering attempt was **the Measure of Economic Welfare** (MEW), which Nordhaus and Tobin (1972) constructed by subtracting negative externalities and adding the value of leisure time and domestic work to the GNP. A more systematic operationalisation was provided by **the Index of Sustainable Economic Welfare** (ISEW) by Daly and Cobb (1989), which is based on personal consumption, adds value to unpaid labour and public goods, and subtracts the costs of income inequality, environmental degradation, depletion of non-renewable resources, and other social costs. **The Genuine Progress Indicator** (GPI) was introduced by Cobb, Halstead, and Rowe (1995) as a revision of the ISEW, with an expanded set of components. It is the most widely used variant of the family and has been applied in dozens of countries and regions. All three variants share the same basic logic: GDP as the starting point, from which the measure of genuine social wellbeing is derived through the monetary valuation of externalities (Goossens et al., 2007).

2.5.3. HDI family

The Human Development Index family represents the most widespread and methodologically consistent family of composite sustainability indicators at the global level. Its origins are linked to Mahbub ul Haq and Amartya Sen, who prepared the first Human Development Report for the UNDP in 1990 (UNDP, 1990). The theoretical basis was Sen's *capability* approach, which understands development not as income growth but as the expansion of human capabilities. **The Human Development Index** (HDI) aggregates three dimensions — health, education, and standard of living — into a single value on a scale of 0–1 using the geometric mean of normalised sub-indices. Owing to the simplicity of its construction and a continuous time series dating back to 1990, the HDI has become the most cited alternative indicator to GDP in the international development discourse.

Despite its success, the basic HDI has been criticised for overlooking distributional aspects, gender differences, and the multidimensional nature of poverty, which has led to the development of a family of adjusted variants. **The Inequality-adjusted HDI** (IHDI), introduced in the 2010 annual report (UNDP, 2010), adjusts the values of all three dimensions by the degree of inequality in their distribution across the population using the Atkinson index. **The Gender Development Index** (GDI), introduced in 2014, compares HDI values separately for women and men and expresses gender parity in terms of human development. **The Multidimensional Poverty Index** (MPI) identifies poverty as a combination of deprivations across the dimensions of health, education, and living standards (Alkire and Foster, 2011).

The latest and, in a paradigmatic sense, the most significant addition to the family is **the Planetary Pressures-adjusted HDI** (PHDI), introduced in 2020 (UNDP, 2020). The PHDI adjusts the HDI using an adjustment factor that reflects CO_2 emissions and the material footprint, thereby linking the social foundation with the ecological ceiling within a single methodological family (Hickel, 2020). The ability to capture all three dimensions of sustainability within a single consistent methodology establishes the unique potential of the HDI family for regional sustainability analysis.

2.5.4. Wellbeing indices

Wellbeing indices share the belief that wellbeing cannot be reduced to economic performance and are based on various conceptual foundations (Figure 2 and Figure 3). Among the most notable of these is **the Happy Planet Index** (HPI), introduced by the UK's New Economics Foundation in 2006, which combines subjective life satisfaction, life expectancy, and ecological footprint into a single score expressing the ecological efficiency of wellbeing (Simms et al., 2006). Thus, the HPI explicitly links social and environmental dimensions. A further example is **Gross National Happiness (GNH),** a concept formulated by the Bhutanese King Jigme Singye Wangchuck in the 1970s, which offers a culturally rooted conception of wellbeing encompassing nine domains ranging from living standards and health to ecological diversity and good governance. The GNH Index is constructed using the Alkire-Foster method across 33 indicators (Ura et al., 2012).

The OECD introduced **the Better Life Index (BLI)**, launched in 2011, following the recommendations of the Stiglitz Commission (Stiglitz, Sen, Fitoussi, 2009), which assesses wellbeing in 38 countries across 11 dimensions, ranging from housing and income to health and the environment (OECD, 2011). The BLI is presented as an interactive dashboard, allowing users to assign their own weights to the dimensions, thereby explicitly acknowledging the normative conditionality of aggregation. **The Social Progress Index** (SPI), developed by Porter, Stern and Green (2014), assesses countries' social and environmental outcomes independently of GDP through basic human needs, foundations of wellbeing and opportunities. The SPI has become an influential tool for policy evaluation, particularly in the context of the SDGs, and has also been adapted for the subnational level; in the EU, this has led to the development of the EU Regional Social Progress Index (EU-SPI), applied to NUTS 2 regions and used including applications by the European Commission for the evaluation of regional policy (De Dominicis et al., 2024).

2.5.5. Subjective indicators

Subjective indicators form a methodologically distinct category that measures wellbeing through respondents' own assessments of their quality of life. The empirical basis for this was laid in the 1970s by the so-called Easterlin paradox, which states that GDP growth does not translate into sustained growth in subjective wellbeing over the long term, a finding that became a key argument for the development of this family of indicators (Easterlin et al., 2010). This concept of Subjective Wellbeing (SWB) was then systematically developed by Diener et al. (1999) as a combination of a cognitive component (*life satisfaction*) and an affective component of emotions. The most widely used measurement tool is the Cantril scale (0–10), employed in the Gallup World Poll and the World Happiness Report (WHR). There is a positive correlation between the World Happiness Index and other development indicators, including the SDG Index (Helliwell et al., 2020; De Neve, Sachs, 2020). Despite growing institutional interest, this family remains an established yet conceptually distinct alternative to other families of sustainability indicators in both academic and political discourse.

2.6. Criteria for the Applicability of Sustainability Indicators

The overview of indicator families in the previous chapter (see Table 2) shows that families differ fundamentally in what they measure, how they measure it, and the purposes for which they were designed. Therefore, the selection of a specific indicator always requires explicit justification in relation to the criteria for applicability. Composite indices represent the most promising tools for monitoring sustainability in terms of communicability and practical usability. By aggregating multiple dimensions into a single value, they offer a comprehensible benchmark (Nardo et al., 2008). However, aggregation inevitably entails methodological costs and may reduce the indicator's informative power. The choice of aggregation method is not technically neutral, as it operationalises an implicit position on the weak–strong sustainability spectrum (Munda, 2005). Therefore, when selecting a composite index, it is necessary to assess not only what it measures but also how it aggregates.

Lepenies (2016) shows that GDP's political dominance stems precisely from its simplicity and unambiguity, characteristics that composite indices partially emulate, while extensive sets of indicators tend to remain confined to academic debate (Sébastien, Bauler, 2013). Therefore, alternative indicators are de facto assessed based on the extent to which they can supplement or replace their informational value (Goossens et al., 2007; Stiglitz, Sen, Fitoussi, 2009). In the EU context, this dimension is of particular relevance: GDP per capita, as the primary allocation criterion for cohesion policy at the NUTS 2 level (European Union, 2003), lacks a social and environmental dimension, which provides a direct argument for the development of alternative indicators at the same territorial level.

The fourth axis is the territorial applicability. As the WISE database demonstrates, all established beyond-GDP metrics are designed at the national level, and subnational applications are predominantly of a case-study nature (Liu et al., 2024). Therefore, territorial applicability significantly narrows the available landscape of families for regional sustainability analysis and defines the central methodological challenge of this study. An integral part of the evaluation is also the discursive presence of the indicator; established presence in the international literature and presence in political discourse distinguish families with documented institutional anchoring from experimental approaches (Böhringer, Jochem, 2007; Jansen et al., 2024).

The underlying framework for these criteria is the coverage of the sustainability dimensions. On the basis of the theoretical analysis above. the method of aggregation, communicability, practical applicability, relationship to GDP, territorial applicability, and discursive presence formed the initial analytical basis for the selection of indicator families in this study. Their application is carried out in the methodology that follows.

3. Methodology

This chapter describes the methodology of the study, from the application of criteria for selecting an indicator family, through the derivation of its regional variants, to their empirical analysis. The criteria are first applied in an evaluation matrix to narrow the indicator families to a smaller group of candidates. These candidates are then assessed in terms of their methodological suitability at the NUTS 2 level, and the availability of data in accessible databases is verified. The regional methodology for the selected family and its adjusted variants is then described, including data sources, the treatment of data gaps, and the calculation of the indices or their proxy-based variants. Finally, functional data analysis is introduced and applied to a pilot set of selected Central European countries.

3.1. Selection of Sustainability Indicator Families

To systematically assess the applicability of the indicator families, an evaluation matrix was compiled by combining four criteria with the author's scoring. The criteria are based on Chapter 2.6: (1) communicability as a single-number composite index comparable to GDP; (2)

relationship to GDP as a reference indicator of regional development; (3) coverage of sustainability dimensions; and (4) discursive presence. The method of aggregation and territorial applicability are not included in the matrix, as they constitute elimination criteria assessed in subsequent steps during the methodological comparison (Chapter 3.2) and the analysis of data availability (Chapter 3.3).

Each of the four criteria is rated on a scale of 1–5, where a score of 5 corresponds to the best possible fulfilment of the criterion and a score of 1 corresponds to its absence or significant limitation. The sum of the scores K1–K4 forms a quantitative basis for comparing the families. In addition to this sum, the matrix includes the author's assessment, which reflects an expert evaluation of overall suitability, considering aspects that the numerical evaluation of individual criteria does not fully capture. The matrix does not represent a weighted index but rather a structured overview that facilitates transparent and reproducible selection. Therefore, the resulting order of families cannot be interpreted as an objective ranking, but as a tool for systematically capturing the author's expert judgement, in accordance with the epistemological approach of Bell and Morse (2008).

3.2. Methodological Comparison of Indicator Families

A methodological comparison of candidate families is conducted along three analytical axes organised according to their eliminatory power in the context of regional sustainability analysis in the EU, serving as a basis for narrowing down the group of candidates for subsequent data availability analyses.

The first axis assesses international acceptability and subnational availability based on the institutional anchoring of the methodology, availability of technical documentation, and existence of proven applications at the subnational level. A systematic Subnational application is considered to be one that covers multiple countries or regions within a single methodological framework.

The second axis assesses the structure of the sub-indicators and their assignment to sustainability dimensions, evaluating whether the family covers all three dimensions simultaneously, only part of them, or whether it has the demonstrable potential to link them through adjusted variants.

The third axis assesses the mathematical basis of the calculation according to the method of normalising input data, the method of aggregating sub-indicators into the final index, and the method of handling missing data. The reference standard for this assessment is the methodological handbook by Nardo et al. (2008).

3.3. Regional nomenclature, data sources and calculation of indices

This chapter describes the regional framework and source databases, the data preparation procedure—including the handling of data gaps and proxy variables—and the general calculation procedure for regional variants of the analysed group. A pilot application was carried out on a set of six Central European EU countries (Germany, Austria, the Czech Republic, Slovakia, Hungary, and Poland) for the period according to the availability of data for individual indicators. The analysis is based on the NUTS 2024 classification (Eurostat, 2026a), which comprises 244 NUTS 2 regions.

3.3.1. NUTS Nomenclature and Regional Framework

The NUTS nomenclature is an EU hierarchical classification system that divides the territory of Member States into four levels: NUTS 0 (countries), NUTS 1 (e.g. federal states in Germany), NUTS 2 (cohesion regions), and NUTS 3 (e.g. counties), with the aim of ensuring the comparability of regional statistics. The NUTS 2 level is the primary analytical level of the EU cohesion policy and serves as the basis for the allocation of funds from the European Structural and Investment Funds (European Union, 2003). The nomenclature is not static; it has undergone several revisions since its introduction, with each change potentially disrupting the consistency of the time series. Therefore, its impact on data continuity is part of the data availability analysis.

3.3.2. Data Sources: Eurostat and EDGAR

The assessment of the feasibility of regional variants of the candidate family at the NUTS 2 level is based on an analysis of the individual indicators for each variant and their comparison with data available in the Eurostat and EDGAR databases. For each variant, an assessment was made as to whether the original indicators could be replaced or approximated using regionally available data while maintaining the methodological basis. The Eurostat database (2026b) provides systematic regional data at the NUTS 2 level for demographic, social, and economic indicators, and the EDGAR database (Crippa et al., 2024) provides data on greenhouse gas emissions at the NUTS 2 level. Data from both databases were manually downloaded into Excel, converted into a uniform format, and linked to an analytical dataset within the R environment (R Core Team, 2025) in the Positron IDE (Posit, PBC, 2024) using the tidyverse package (Wickham et al., 2019).

3.3.3. Data Gaps and Imputation Methods

Data completeness was verified for each sub-indicator and region separately. In addition to discontinuities, reasons for data unavailability include changes in the NUTS nomenclature, delays in data reporting by Member States, insufficient statistical reliability of data for small regions, or incomplete coverage of certain indicators over time. Therefore, it was necessary to analyse data gaps and impute missing data. Data gaps were imputed using three methods, depending on the nature and extent of the missing values. Direct imputation from a higher-level administrative unit (NUTS 1 or NUTS 0) is used where a region has no or almost no data of its own. The proportional method also works with data from a higher-level unit, but to preserve the trend of the time series, it uses the average ratio of the region's values to those of the higher-level unit from years for which data are available and applies this ratio to the missing periods. If NUTS 1 data are unavailable, NUTS 0 is used. Linear interpolation or extrapolation is used for short gaps not exceeding three years, with the first or last five available values of the time series serving as the basis for the trend.

3.3.4. Proxy Indicators and Approximations

For use at the regional level, it must be considered that some data described in the original methodologies are not available at all or are available only at the national level. Proxy substitutes were therefore sought, or conversions using similar indicators were adopted; the details are described directly for the individual sub-indicators. Although the derived variables do not fully correspond to the original methodology, they are capable of indicating trends and relative differences between regions; however, they cannot replace direct statistical measurements at the NUTS 2 level. Where data or methodological constraints prevent full adherence to the original methodology, the aim is to demonstrate these indicators' regional applicability and usefulness rather than provide definitive measurements.

The calculations, based on the original or modified methodologies, were performed in the R environment (R Core Team, 2025) within the Positron IDE (Posit, PBC, 2024). A detailed computational procedure, including the derivation formulas for the proxy indicators and all four variants of the regional index, is provided in Appendix C.

3.4. Functional Data Analysis and Global Envelope Tests

The results of the calculations of the regional variants of selected indicators for each region were transformed into a time series format suitable for functional data analysis. The data are organised so that each region is represented as a single functional object in the form of a continuous trajectory capturing its development over time. This approach allows patterns to be identified that differ not in value but in the shape of their development. Three tools are introduced in turn: functional boxplots for visualising trajectories, global envelope tests for statistical verification of differences between groups of regions, and difference curve analysis for identifying outlier trajectories.

3.4.1 Functional Boxplots

A functional boxplot (fBoxplot from the GET package; Myllymäki, Mrkvička, 2023) was constructed separately for each index variant. Similar to a classic boxplot, it displays three components: the median trajectory as a curve with the greatest depth according to the Extreme Rank Length (ERL) method as a functional equivalent of the median; a band of variability enclosing 50 % of the central trajectories as a functional equivalent of quartiles; and outlier trajectories representing regions whose development differs significantly from the rest of the group. A comparison of functional boxplots across index variants allows the assessment of how the choice of indicator influences the overall dynamics of regional development, the degree of variability between regions, and the identification of atypical trajectories. Visualisations were created using the ggplot2 package (Wickham, 2016).

3.4.2 Global Envelope Tests

The global envelope test (the global_envelope_test function from the GET package; Myllymäki, Mrkvička, 2023) was used for the formal statistical verification of the hypothesis regarding the equality of the distributions of the trajectories of the two groups of regions. The test compared the distribution of trajectories of both groups and calculated a simultaneous confidence envelope, an interval that, with a given probability, contained all observed differences between the groups at every time point. If the null hypothesis of equality of trajectory distributions is true, the observed difference should lie within the envelope; exceeding the envelope at a certain point on the time axis indicates a statistically significant difference between the groups during that period. The result of the test is a p-value that expresses the probability that the observed differences could have arisen by chance if the null hypothesis were true. The significance level was set at $\alpha = 0{,}05$, with 999 permutations, the minimum achievable p-value is 0,001. Comparing test results across index variants allows us to assess whether conclusions about differences in trajectories depend on the choice of the indicator (Myllymäki et al., 2017).

3.4.3 Difference Curves and Outlier Analysis

The difference curve analysis evaluates each region individually against the distribution of the entire dataset. For each index, the deviation of the regional curve from the median trajectory is calculated; positive values indicate regions that were consistently above average and negative values indicate regions that were consistently below average. By displaying the entire series of difference curves for all regions simultaneously, it is possible to capture the distribution of deviations within a single indicator and compare patterns of environmental penalisation or gender gaps between different index variants. The grey area delineates the 90 % central region defining the interval within which 90 % of the regional curves with the highest functional depth according to the ERL method fall. Regions whose trajectories lie consistently outside this envelope are marked as functional outliers — blue for regions consistently above average and red for regions consistently below average.

Calculations were performed using R software (R Core Team, 2025) in the Positron IDE (Posit, PBC, 2024), utilising the tidyverse (Wickham et al., 2019) and ggplot2 (Wickham, 2016) packages. All three methods are demonstratively applied to a pilot sample of 84 NUTS 2 regions across six Central European EU countries: Germany, Austria, the Czech Republic, Slovakia, Hungary, and Poland.

4. Results

This chapter presents the research results in steps corresponding to the methodological structure of Chapter 3: application of the evaluation matrix to nine indicator families (4.1), methodological comparison of candidate families and identification of the HDI family (4.2), verification of data availability for regional variants of the HDI (4.3), calculation of regional variants of the index (4.4) and the results of the functional data analysis (4.5).

4.1. Assessment of Sustainability Indicator Families

By applying the assessment matrix described in Chapter 3.1 to the nine families of sustainability indicators from Chapter 2.5, the following results were obtained (Table 3).

Table 3: Assessment of Sustainability Indicator Families

Family	K1	K2	K3	K4	Author's rating	Justification	Sum	Rank
GDP *(ref.)*	5	-	1	5	-	Reference point; one-dimensional; S and Env missing	**-**	**-**
1 Green economy	3	4	2	2	2	Strong link to GDP; predominantly E+Env; low public awareness	**11**	**7**
2 Ecological Footprint (EF)	4	2	2	4	3	Strong Env; no S or E; key HDI supplement via PHDI	**12**	**5**
3 Environmental performance	3	2	2	3	1	Narrow sector; excluding S and E	**10**	**9**
4 GPI/ISEW	4	5	4	2	3	All dimensions; methodological heterogeneity; low awareness	**15**	**4**
5 HDI family	5	4	4	5	5	S+E strong; PHDI integrates Env via EF; long history	**18**	**2**
6 Wellbeing indices[2]	4	3	3	3	3	S+W strong; Env weak	**13**	**6**
7 SDG Index	4	3	5	4	4	Broadest coverage of dimensions; complexity reduces communicability	**16**	**3**
8 Indicator sets	2	3	5	3	2	Full coverage; not a composite index	**13**	**7**
9 Subjective	3	1	2	3	2	S+W only; survey data	**9**	**8**
5+2 HDI+EF	5	4	5	5	5	A combination covering all dimensions; operationalised via the PHDI (UNDP, 2020)	**19**	**1**

Source: Authors' own assessment.

Note: Scale 1–5, where 5 = best. K1 = communicability as a single-number composite index; K2 = relationship to GDP; K3 = coverage of sustainability dimensions (E = economic, S = social, Env = environmental); K4 = discursive presence (public awareness and length of history).

4.2. Methodological Comparison of Candidate Indicator Families

4.2.1. Comparative Assessment across Key Methodological Dimensions

The four candidate families—the HDI family, the SDG Index, the Ecological Footprint, and the GPI/ISEW—are compared in Table 4 along three analytical axes: institutional anchoring and availability at the subnational level, the structure of component indicators and coverage of sustainability dimensions, and the mathematical basis of the index construction. The reference

[2]No 6 includes the EU Regional Social Progress Index (EU-SPI; De Dominicis et al., 2024); while thematically close, it was not advanced further as it intentionally excludes the economic dimension and does not provide a time series suitable for functional data analysis."

standard for the assessment is the methodological guide by Nardo et al. (2008) in terms of normalisation, aggregation, and weighting.

Table 4: Methodological Comparison of Candidate Indicator Families

Criterion	HDI family	SDG Index	Ecological Footprint	GPI/ISEW
Institutional anchoring	UNDP since 1990	SDSN since 2015	GFN	Academic
Subnational applications	2 systematic	Cities only	-	-
Coverage of dimensions	Soc+E+(Env via PHDI)	E+Soc+Env	Env only	E+Soc+Env
Normalisation	Min-max	Min-max	Biophysical	Monetary
Aggregation	Geometric mean	Arithmetic mean	Sum	Sum
Consistency with Nardo et al. (2008)	High	Medium	Low	Low–medium

Source: Authors' own compilation based on UNDP (2024), Lafortune et al. (2018), GFN (2023), Cobb et al. (1995), Van der Slycken, Bleys (2023) and Nardo et al. (2008).

4.2.2. Synthesis: Selection of the HDI Family

The evaluation matrix (Table 4) and methodological comparison (Table 5) jointly identified the HDI family as the most suitable basis for subsequent regional analysis. The SDG Index offers the broadest coverage of sustainability dimensions and strong institutional anchoring; however, its application at the NUTS 2 level has not yet been implemented, and the high number of sub-indicators (126) presents a significant barrier to data availability at the regional level. The Ecological Footprint provides a robust measure of the environmental dimension but lacks social and economic dimensions, and its subnational applications are exclusively case studies without a unified methodological framework. The GPI/ISEW, as the only family alongside the HDI covering all three dimensions in parallel, exhibits high methodological heterogeneity across studies, and the absence of a global umbrella institution hinders the standardisation necessary for systematic application.

In terms of compliance with the methodological standard set out by Nardo et al. (2008), the HDI family shows the highest degree of compliance, using min-max normalisation, a geometric mean to prevent full substitution of dimensions, equal weights, and systematic imputation of missing data. The same applies to the adjusted and regional variants of the HDI; the environmental component of the PHDI further enhances the robustness of the index. The SDG Index achieves moderate consistency, where normalisation complies with the standard, but the arithmetic mean as an aggregation method allows for the substitution of the dimensions. The Ecological Footprint and GPI/ISEW show low agreement. Both use absolute values instead of min-max normalisation and an arithmetic sum with expert-determined or productivity-based weights. The GPI/ISEW is additionally burdened by high subjectivity in the choice of weights and the sensitivity of proxy estimates for missing data. GPI 2.0 improves partial compliance through a revised weighting system (Talberth, Weisdorf, 2017); however, even this update does not address the absence of systematic subnational application.

In contrast, the HDI family meets all three comparison criteria: it has the strongest institutional foundation (UNDP since 1990), comprehensive technical documentation, the geometric mean as its aggregation method, and two systematic subnational applications covering EU NUTS 2 regions (Hardeman, Dijkstra, 2014; Smits, Permanyer, 2019). The environmental dimension, which is absent from the basic HDI, is integrated via the PHDI (UNDP, 2020), and CO_2 emissions data from the EDGAR database can be utilised (Crippa et al., 2024).

4.2.3. HDI Family Variants: Sub-indicators, Methodology and Data Availability

The starting point for assessing the applicability of the adjusted HDI variants at the regional level is an overview of the entire family, according to the UNDP Technical Notes (UNDP, 2024) (Table 5). For each variant, an assessment was made as to whether the original UNDP indicators could be replaced or approximated using regionally available data while maintaining the methodological basis (Hardeman, Dijkstra, 2014). On this basis, an assessment of the regional applicability of individual variants for the NUTS 2 level will subsequently be carried out, identifying the available data sources and necessary methodological compromises.

The R-HDI (Hardeman, Dijkstra, 2014) was developed at the request of the European Commission and covers all NUTS 2 regions based on Eurostat data with dynamic goalposts derived from European regional data, thereby maintaining sensitivity to capture intra-European disparities. The SHDI covers 1,625 regions across 161 countries with regular updates via the Global Data Lab; however, it has two limitations in the EU context: an inconsistent territorial level (a combination of NUTS 1, NUTS 2 and NUTS 3) and global goalposts causing compression of values at the top of the scale (Smits, Permanyer, 2019).

An overview of all the HDI family's variants, including their sub-indicators and data sources for the NUTS 2 level, is provided in Table 6, which also serves to identify the variants proceeding to the empirical section.

Table 5: Overview of HDI Family Indicators Including Existing Regional Variants

Variant	Dimensions	Indicators	In addition to / differing from the HDI
HDI	Health	Life expectancy at birth	-
	Education	Expected years of schooling; Mean years of schooling	
	Income	GNI per capita (PPP, 2017 $)	
IHDI	All	Same as HDI	+ Atkinson inequality index for all three dimensions
GDI	All	Same as HDI	+ Gender disaggregation of all indicators (F/M); + Female/Male estimated earned income per capita
GII	-	Different from HDI	Maternal mortality ratio; Adolescent birth rate; Share of parliamentary seats (F/M); Secondary education (F/M); Labour force participation (F/M)
PHDI	All + Env.	Same as HDI	+ CO_2 emissions per capita; + Material footprint per capita
MPI	-	Different from HDI	Nutrition; Child mortality; Years of schooling; School attendance; Electricity; Sanitation; Water; Housing; Cooking fuel; Assets
SHDI	All	Same as HDI	Subnational level corresponds to NUTS 1–3 in the EU; global benchmarks UNDP; outside the EU according to local regional structure
R-HDI	Health	Life expectancy at birth; Infant mortality rate	Adapted by Eurostat for NUTS 2; dynamic goalposts
	Education	NEET rate; Tertiary education	
	Income	Net disposable household income per capita; Employment rate	

Source: Authors' own compilation based on UNDP (2024), Smits and Permanyer (2019), Hardeman and Dijkstra (2014).

Table 6: Sub-indicators of Regional HDI Variants and Data Sources

Variant	Dim.	Regional indicator for NUTS 2	Source / Code
R-HDI	H	Life expectancy at birth	Eurostat demo_r_mlifexp
		Infant mortality	Eurostat demo_r_minf
	Ed	NEET rate	Eurostat edat_lfse_22
		Proportion of people with tertiary education	Eurostat edat_lfse_04
	I	Net disposable household income pc	Eurostat tgs00026
		Employment rate	Eurostat lfst_r_lfe2emprt
R-IHDI	H+Ed+I	+ dimensionality reduction using the Atkinson index	R-HDI + calculation of AI from inter-regional distribution
R-GDI	H+Ed+I	R-HDI + Gender disaggregation (F/M) + Female/Male estimated earned income per capita	Eurostat / LFS
R-GII	-	Maternal mortality; Adolescent birth rate; Parliamentary seats; Secondary education; LFPR	-
R-PHDI	H+Ed+I+Env	+ CO_2 emissions per capita	EDGAR
		MF proxy — national MF disaggregated by industrial employment weights (sectors B–F)	Eurostat env_ac_mfa + lfst_r_lfe2en2
MPI	-	Nutrition; Child mortality; Schooling; Sanitation; Water; Housing; Assets	-
SHDI	H+Ed+I	Same methodology as HDI; data from national statistics	National statistics; various NUTS levels 1–3

Source: Authors' own compilation based on UNDP (2024), Hardeman and Dijkstra (2014), Smits and Permanyer (2019), Crippa et al. (2024).

Notes: H = health; Ed = education; I = income; Env = environmental dimension.

Four feasible variants will proceed to the empirical section in Chapter 4.3: R-HDI as a fully feasible basis, R-IHDI as an exploratory approximation of inter-regional disparity and R-GDI operationalised through its gender components (R-HDI_F and R-HDI_M) rather than as a GDI ratio, and R-PHDI in two tested variants — single-component (CO_2 from EDGAR only) and two-component (CO_2 + MF proxy).

4.3. Data Availability for NUTS 2 in Eurostat for Selected Indicators and Countries

4.3.1. Impact of NUTS Changes on Time Series Continuity

The NUTS classification has evolved in parallel with the enlargement of the European Union and the adaptation of Member States' administrative structures.The number of regions at each NUTS level is not constant, and every revision of the classification represents a potential discontinuity for historical time series.

The number of Member States (NUTS 0) rose from 14 in 1995 to 27 in 2003 following EU enlargement and remained at this level following the UK's withdrawal under Brexit. The number of NUTS 1 regions increased from 66 (1995) to 92 (2016–2024), with the largest increase occurring between 2003 and 2006 (15 new units). The number of NUTS 2 regions expanded from 171 (1995) to 244 (2024), with a significant jump of 57 regions between 1999 and 2003, caused by the preparation of the NUTS classification for the 2004 EU enlargement

For the purposes of this study, the periods after 2003 are particularly relevant. Although the numbers appear stable, even minor changes (mergers, divisions, renaming of individual regions) can disrupt the continuity of data for specific Member States.

Of the six countries selected for analysis, Germany, Hungary, and Poland, in particular, show territorial changes at the NUTS 2 level that affect the continuity of the time series. In this context, the impact on continuity distinguishes between changes that disrupt time series (*Split, Merged, Terminated*) and administrative changes with no impact (*Rename, Code change, Boundary shift*). Between 1999 and 2010, Germany underwent four waves of changes affecting the continuity of time series:

- DED0 Saxony split into DED1, DED2 and DED3 (1999)
- DE40 Brandenburg split into DE41 and DE42 (2003), then merged back into DE40 in 2010
- the three parts of DEE0 Saxony-Anhalt merged into a single region (2006)
- DED1 and DED3 renumbered as DED4 and DED5 with boundary adjustments (2010)

Since 2010, the structure of Germany's 38 regions has remained stable. For the other countries in the pilot sample, changes affecting continuity were limited.

- Hungary: HU10 Közép-Magyarország split into HU11 Budapest and HU12 Pest (2013–2016)
- Poland: PL12 Mazowieckie split into PL91 Warszawski stołeczny and PL92 Mazowiecki regionalny + 5 code changes (2013–2016)
- Austria: two name changes to AT11 Burgenland with no impact on data continuity
- Czech Republic and Slovakia: no changes throughout the entire period under review

4.3.2. Availability of Data Sources for Regional HDI Variants

The availability of data for calculating regional HDI variants was verified for all sub-indicators in the Eurostat and EDGAR databases for the period covered by this pilot study. Table 7 provides an overview of all data sources used, their assignment to individual index variants, and time coverage.

Table 7: Data Sources for Regional HDI Variants — Coverage and Index Assignment

Dataset	Code	R-HDI	R-IHDI	R-GDI	R-PHDI	Availability
Life expectancy	demo_r_mlifexp	✓	✓	✓ F/M	✓	1990–2024
Infant mortality NUTS 2	demo_r_minfind	✓	✓	proxy	✓	1990–2024
Infant mortality NUTS 0	demo_minfs	—	—	✓ F/M	—	2007–2024
NEET	edat_lfse_22	✓	✓	✓ F/M	✓	2000–2025
Tertiary education	edat_lfse_04	✓	✓	✓ F/M	✓	2000–2025
Household income	nama_10r_2hhinc	✓	✓	base	✓	2000–2024
Employment rate	lfst_r_lfe2emprt	✓	✓	✓ F/M	✓	1999–2025
Labour force Y15-64	lfst_r_lfp2act	—	—	EAf/EAm	—	1999–2025
Gender pay gap	earn_gr_gpgr2	—	—	Wf/Wm	—	2007–2024
Population F/M	demo_r_pjangroup	—	—	Pf/Pm	—	1990–2025
GHC, CO_2 equivalent	EDGAR_2024_total_GHG_AR5	—	—	—	Var A	1990–2023
Industrial employment B–F	lfst_r_lfe2en2	—	—	—	Var B	2000–2024
Material flow accounts	env_ac_mfa	—	—	—	Var B	2015–2024
Fossil CO_2	EDGAR_2024_GHGs CO2eq_AR5	—	—	—	Var B	1990–2023

Source: Author's own compilation based on Eurostat (2026) and Crippa et al. (2024).

Note: ✓ = indicator used in the variant; ✓ F/M = gender disaggregated (Female/Male); proxy = approximated from national data; EAf/EAm = economically active population share (F/M, Y15-64); Wf/Wm = gender wage ratio (NUTS 0, sectors B–F); Pf/Pm = female/male population share; NUTS 0 = national level only. R-PHDI A = single-component variant (CO_2 from EDGAR only); R-PHDI B = two-component variant (CO_2 + material footprint proxy).

4.3.3. Data preparation and data gaps

The source data for calculating all four regional HDI were downloaded from the Eurostat and EDGAR databases. An overview of all datasets used, including their assignment to index variants and time coverage, is presented in Table 7.

Three sub-indicators are not directly available at the NUTS 2 level and were approximated from data at a higher territorial level. Infant mortality by sex (InfMort_F, InfMort_M) was derived from the total regional value and national sex ratio from the demo_minfs database (NUTS 0). Household income by sex (HHInc_F, HHInc_M) was derived from the total HHInc value at the NUTS 2 level, the proportion of the economically active population by sex, and the gender pay gap available at the NUTS 0 level. The material flow (MatFlw) for Variant B of the R-PHDI was derived from the national material flow data disaggregated using the region's share of industrial employment (sectors B–F, and is available only for the period 2015–2023.

Detailed derivation formulas are provided in Appendix C. All derived variables reflect trends and relative differences between regions but cannot replace direct statistical measurements at the NUTS 2 level.

Data gaps were identified separately for each indicator and each region and filled using three methods, depending on the nature and extent of the missing values (see 3.3.3): direct imputation from a higher-level administrative unit (NUTS 1 or NUTS 0) for regions without their own data, the proportional method for longer systematic gaps, and linear interpolation or extrapolation for short gaps of up to three years. Regions with extensive gaps were retained in the analysis for comparability; however, their interpretation requires increased caution; the potential impact of imputation on the GET results is assessed by an orientational sensitivity check in Section 4.5.2. The extent of data gaps and the imputation methods used are summarised in Table 8 for the baseline R-HDI data at the country level; the same evaluation was performed for the Female and Male variants. Detailed data by indicator and gender variant are available from the authors upon request.

Table 8: Data Gaps and Imputation Methods by Country for R-HDI Sub-indicators

Country	Total Data (n)	Total Gaps (n)	Missing (%)	Direct imputation (n)	Proportional method (n)	Linear approximation (n)
CZ	200	16	1,3	0	0	16
DE	950	880	15,4	456	136	288
HU	200	12	1,0	0	0	12
AT	225	42	3,1	25	0	17
PL	425	327	12,8	0	259	68
SK	100	19	3,2	0	7	12
Total	**2100**	**1315**	**10,3**	**481**	**402**	**413**

Source: Author's own calculations based on Eurostat (2026b).

Table 8 shows that the distribution of data gaps is highly uneven across countries. Germany has the highest number of gaps (880, i.e. 15,4 %), filled mainly by direct imputation from a higher-level unit and linear approximation; Poland is second (327 gaps, 12,8 %) with a predominance of the proportional method. The other countries show a low proportion of gaps: the Czech Republic (1,3 %) and Hungary (1,0 %) exclusively by linear approximation, Austria (3,1 %) by direct extrapolation, and Slovakia (3,2 %) by the proportional method.

4.4. Normalisation of sub-indicators and calculation of indices

The normalisation of sub-indicators represents the first step in calculating regional variants of the HDI for the three basic datasets (Basic, Female, and Male), which form a common basis for the calculation of all four variants of the index (R-HDI, R-IHDI, R-HDI_F, R-HDI_M, and R-PHDI).

To determine the normalisation bounds, the source time series was extended by linear projection to the years 2025–2029, and the goalposts were set as global extremes across all regions and all years, including the projected years, thereby ensuring the stability of the index against future data. For sub-indicators with a negative trend (InfMort, NEET), negative projected values were truncated to zero. The goalposts were first derived separately for each of the three variants and were subsequently unified. Four values from the Female and Male variants lay outside the range of the Basic set of sub-indicators: maximum life expectancy for women (85,7 years), maximum proportion of women with tertiary education (82,1 %), minimum household income for women (€2,351), and maximum employment rate for men (96,1 %). The resulting common goalposts used for the normalisation of all three variants are listed in Table 9.

Table 9: Final Common Goalposts for Normalisation of R-HDI, R-GDI_F and R-GDI_M

Indicator	Direction	Min	Max	Source
LifeExp	positive	67,6	85,7	Male min, Female max
InfMort	negative	0	13,0	Basic (adjusted)
NEET	negative	0	33,0	Basic (adjusted)
TertEdu	positive	6,5	82,1	Basic min, Female max
HHIncome	positive	2 351	33 413	Female min, Basic max
EmpRate	positive	47,3	96,1	Female min, Male max

Source: Authors' own calculations based on Eurostat (2026b).

The lowest values were recorded in the eastern regions of Slovakia and Hungary at the start of the period under review: the lowest life expectancy (71,2 years), the lowest household income (€2,351), the highest infant mortality rate (13 **‰**), and the NEET rate (33 %). The maximum values correspond to the 2029 projection, for example, the highest life expectancy for women (85,7 years) in Vorarlberg, Austria, the highest household income (€33,413) in Upper Bavaria, and the highest male employment rate (96,1 %) in Dresden, Saxony.

The sub-indicators were normalised to the 0–1 interval using the min-max method with these common goalposts. Specific adjustments to the formulas were applied for the actual calculation. For sub-indicators with a positive trend (LifeExp, TertEdu, HHIncome, EmpRate) and for sub-indicators with a negative trend (InfMort, NEET), the inverse formula was used, as described in Appendix C.

All four variants of the regional human development index were calculated based on normalised sub-indicators. The R-HDI was determined as the geometric mean of the three dimensional indices (health, education and income), with each dimensional index representing the arithmetic mean of the two relevant normalised sub-indicators. The R-GDI was derived as the ratio of R-HDI_F to R-HDI_M; a value of 1 indicates gender parity, values below 1 indicate a disadvantage for women, and values above 1 indicate a disadvantage for men. However, because functional data analysis requires continuous trajectories rather than ratios, *the gender dimension was examined through the separate analysis of R-HDI_F and R-HDI_M trajectories rather than the R-GDI ratio itself.*[3]

The inequality-adjusted variant (R-IHDI) was constructed as a methodological innovation adapting the UNDP approach to the regional level. Given the absence of microdata on the distribution of income, education, and health within regions, Atkinson's measures of inequality were calculated from the distribution of dimensional indices across regions for each year. The R-IHDI constructed in this way represents a simulation of inter-regional disparity rather than a measure of individual inequality within regions; its values should therefore not be interpreted as an absolute expression of inequality but as an illustration of a trend.

The regional planetary pressures-adjusted index (R-PHDI) was calculated using two variants. Variant A uses total greenhouse gas emissions from the EDGAR database for the period 2000–2024, with the year 2024 being estimated using a linear projection. Variant B combines CO_2 emissions and a derived material flow indicator for the shorter period 2015–2023 and is therefore purely a model. It should be noted that the original UNDP PHDI is based on production-based fossil CO_2 emissions and material footprint; neither variant is therefore directly comparable with the UNDP PHDI, and both serve primarily to demonstrate the applicability of the environmental adjustment approach at the NUTS 2 level. In all variants, the adjustment factor was constructed analogously to the UNDP methodology as a normalised environmental index by which the R-HDI is multiplied, with the difference between the R-HDI and the R-PHDI expressing the percentage loss in the index value caused by planetary pressures.

[3] The shift from the R-GDI indicator to a separate analysis of the R-HDI_F and R-HDI_M indices reflects a methodological limitation: the analysis of functional data relies on continuous trajectories, whereas the R-GDI ratio does not allow for such comparisons. The gender dimension is therefore operationalised through sub-indices throughout the empirical analysis.

Calculations for all four variants were performed in the R environment (R Core Team, 2025) within the Positron IDE (Posit, PBC, 2024), using the tidyverse package (Wickham et al., 2019). The calculated index values are available as Excel spreadsheets upon request from the author. Descriptive statistics for all four variants of the index, also produced in R, are presented in Appendix A. Descriptive Statistics of the R-HDI Index Family

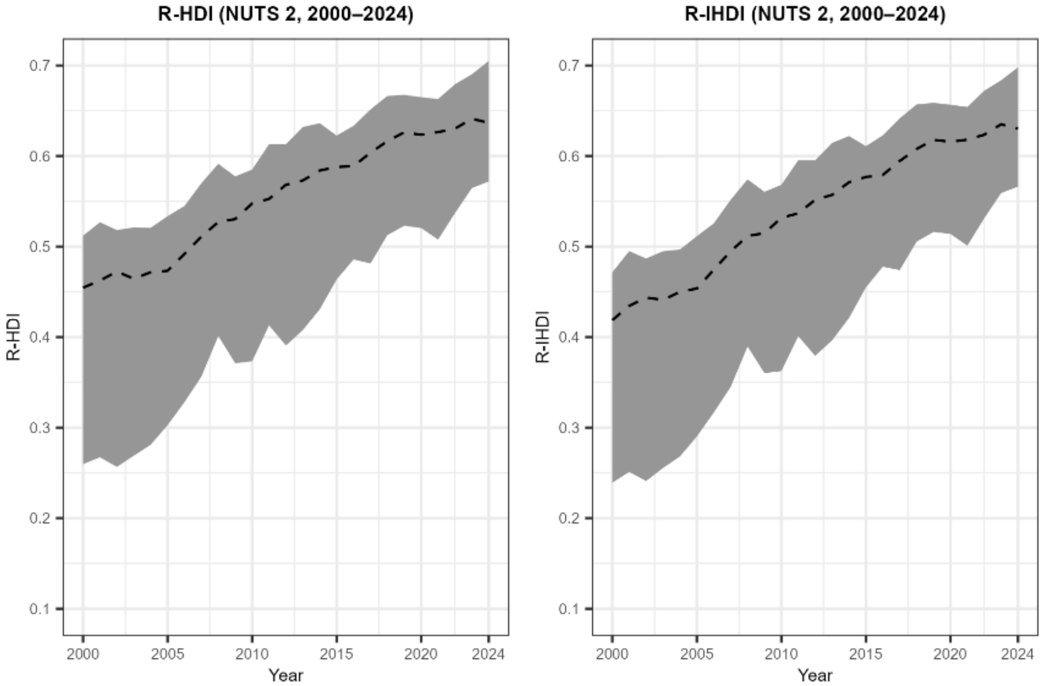
4.5. Results of Functional Data Analysis

Functional data analysis (FDA) was applied to the time series of all constructed variants of the R-HDI index for a pilot sample of 84 NUTS 2 regions (DE, AT, V4) for the available periods. All three analytical tools, functional boxplots (4.5.1), global envelope tests (4.5.2) and difference curve analysis (4.5.3), are implemented in the GET (Myllymäki, Mrkvička, 2023) in the R environment and utilise the Extreme Rank Length (ERL) method to calculate functional depth.

4.5.1. Functional Boxplots of the R-HDI Index Family

Functional boxplots of the R-HDI and R-IHDI (Figure 4) were constructed from time series for 84 NUTS 2 regions covering the period 2000–2024. The functional median of the R-HDI rose from approximately 0,46 in 2000 to 0,64 in 2024, with the 50 % central range gradually narrowing over the period under review, indicating convergence among the regions in the pilot sample. Two distinct fluctuations are evident: a decline in the period 2008–2010 (the global financial crisis) and stagnation in the years 2019–2021 (COVID-19). The R-IHDI shows systematically lower values, although the difference compared to the R-HDI is small. This result reflects the methodological limitations of the calculation at the NUTS 2 level: without microdata on the distribution of income, education, and health within regions, the Atkinson inequality index cannot be fully applied in accordance with the UNDP methodology. Therefore, the R-IHDI graph is interpreted as an illustration of this limitation, not as a fully fledged result.

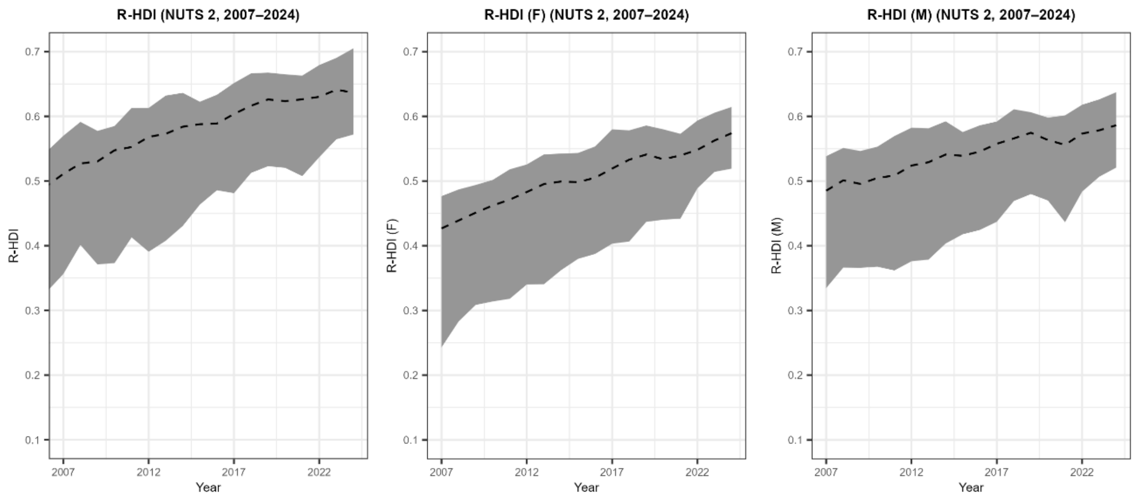
Figure 4: R-HDI and R-IHDI: Functional Boxplots, NUTS 2 (DE, AT, V4)



Source: Authors' own calculations based on Eurostat

The gender components R-HDI_F and R-HDI_M were calculated separately for the period 2007–2024 and compared with the overall R-HDI (Figure 5). The overall R-HDI is systematically higher than both gender components, as each component is penalised by its own weaknesses (lower income for women, shorter life expectancy for men), while the overall index averages out these effects. R-HDI_M exceeds R-HDI_F throughout the entire period under review, with the difference driven by income. The functional medians of both components converged, and the 50 % central ranges narrowed, suggesting a trend towards convergence. A wider central range of R-HDI_F indicates greater regional heterogeneity in the female component of the index.

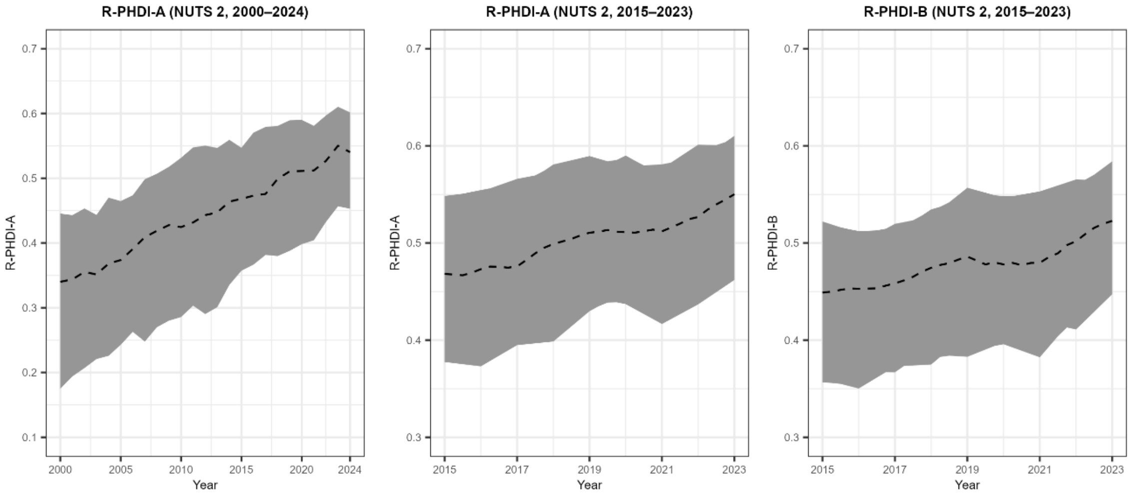
Figure 5: R-HDI by Gender: Functional Boxplots, NUTS 2 (DE, AT, V4)



Source: Authors' own calculations based on Eurostat data.

The planetary pressures-adjusted variants R-PHDI-A and R-PHDI-B were compared over the entire available period and also within the common time window of 2015–2023 (Figure 6). R-PHDI-A is constructed by adjusting the R-HDI for greenhouse gas emissions expressed in CO_2 equivalents (CO_2eq) from the EDGAR database, whereas R-PHDI-B combines fossil $CO_2$with the material footprint (MF). The functional median of the R-PHDI-A is lower than that of the R-HDI throughout the period by approximately 0,05–0,10 points, with the difference increasing slightly over time, in line with the growth in the absolute values of the index. Over the comparative period 2015–2023, the R-PHDI-B consistently shows lower values than the R-PHDI-A by approximately 0,02–0,03 points and a narrower 50 % central range; the material footprint thus adds a penalising effect beyond the adjustment for greenhouse gas emissions and simultaneously homogenises the distribution of regional values across the pilot regions. Both indices are sensitive to economic shocks, with the decline in 2019–2021 being more pronounced for R-PHDI-B, reflecting the material footprint's faster response to a decline in economic activity.

Figure 6: R-PHDI Variants: Functional Boxplots, NUTS 2 (DE, AT, V4)



Source: Authors' own calculations based on Eurostat and EDGAR data

A numerical comparison of trends across all index variants is summarised in Table 10, which presents the functional medians over five-year periods. The values were consistent with the course of the median curves in the functional boxplots. An upward trend was evident for all index variants throughout the review period. The most pronounced penalisation effect is exhibited by R-PHDI-A, whose values are the lowest of all variants available for a given time window in each period. Detailed descriptive statistics are provided in Appendix A.

Table 10: Functional median of the R-HDI family, NUTS 2 regions, 2000–2024

Period	R-HDI	R-IHDI	R-HDI (F)	R-HDI (M)	R-PHDI-A	R-PHDI-B
2000–2004	0,463	0,434	—	—	0,352	—
2005–2009	0,509	0,490	—	—	0,395	—
2010–2014	0,562	0,546	—	—	0,439	—
2015–2019	0,603	0,593	0,444	0,501	0,484	0,460
2020–2024	0,632	0,625	0,498	0,534	0,529	0,495

Source: Authors' own calculations based on Eurostat data.

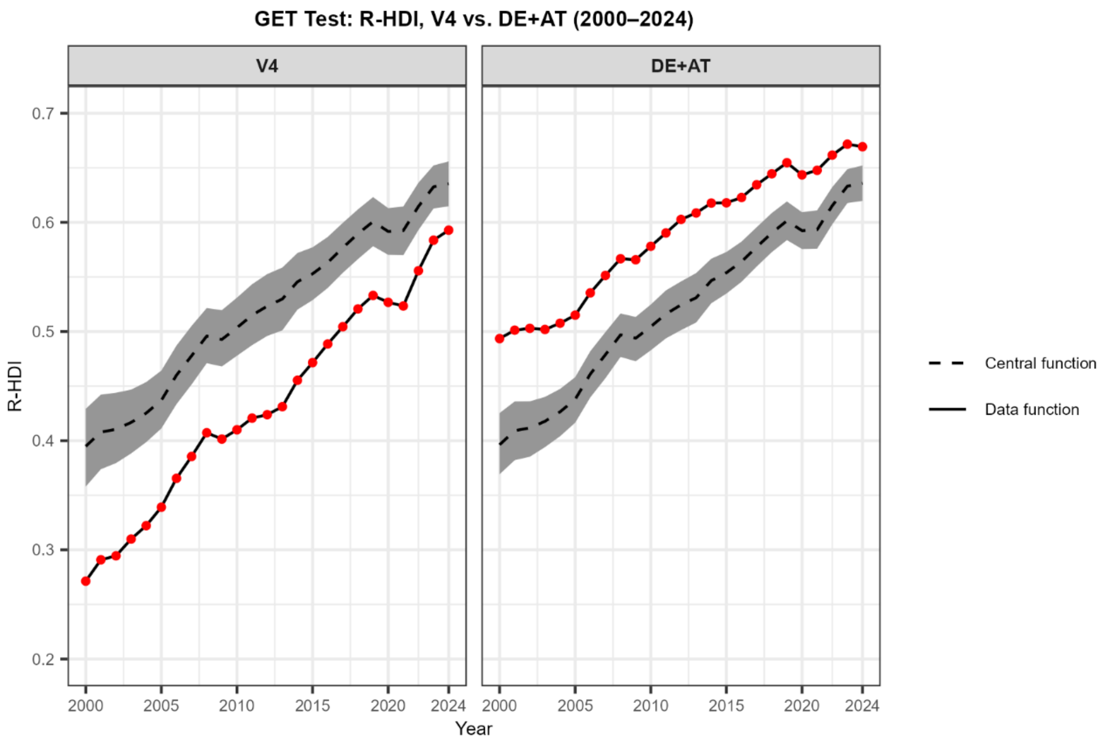
Note: Values represent the functional median (curve with the deepest ERL). Full descriptive statistics are provided in Appendix A.

4.5.2 Global Envelope Test: V4 vs. DE+AT Regions

The global envelope test (GET) was applied to the R-HDI and R-PHDI-A time series to formally verify whether the trajectories of the V4 regions (CZ, SK, HU, PL) differed statistically from those of the DE+AT group (DE, AT). Testing the two indices allows us to assess whether environmental adjustment for greenhouse gas emissions in CO_2 equivalents alters the nature of the differences between the two groups.

The test was first applied to the R-HDI time series. Figure 7 shows the test results in two panels: the left panel for the V4 group and the right panel for the DE+AT group. In each panel, the dashed line represents the group's central function (functional median using the ERL method), the grey area delineates the 95 % simultaneous confidence envelope constructed on the basis of 999 permutations, and the curve with red dots displays the observed average group curve (data function). Exceeding the envelope indicates a statistically significant difference that cannot be explained by the random permutation of group assignment. The test result unequivocally rejected the null hypothesis of congruence between the trajectories of both groups (p = 0,001): the observed average curve lay outside the 95 % envelope at all 25 time points for both groups. The V4 regions consistently achieve lower R-HDI values than the DE+AT regions throughout the entire period under review (2000–2024), with the difference gradually narrowing over time — a trend of convergence is particularly evident after 2015, when the growth rate of the V4 regions exceeds that of the DE+AT regions. An orientational sensitivity check restricting the analysis to the period 2012–2024, which contains substantially fewer imputed values, produced comparable estimates (p = 0.001), providing some reassurance that the main GET finding is not substantially influenced by the imputation of missing values.

Figure 7: GET Test: R-HDI, V4 vs. DE+AT, NUTS 2 Regions, 2000–2024 (p = 0,001)

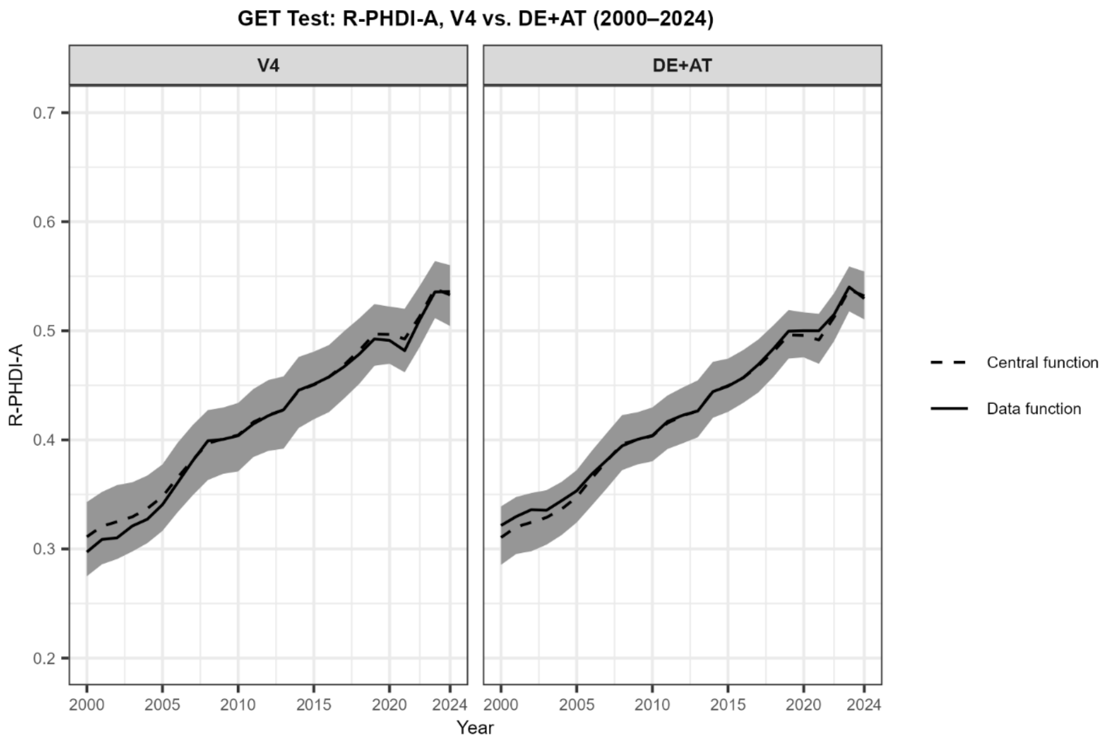


Source: Authors' own calculations based on Eurostat data.

Note: Dashed line = central function (functional median, ERL depth method); shaded area = 95 % simultaneous confidence envelope based on 999 permutations; red line with points = observed mean curve (data function).

The same test was applied to the R-PHDI-A time series. Figure 8 shows the results in the same format as Figure 7. The test result differed fundamentally from that for the R-HDI: the null hypothesis of trajectory congruence was not rejected (p = 0,487), and the observed mean curve lay within the 95 % envelope at all 25 time points for both groups. Following environmental adjustment for greenhouse gas emissions, the statistically significant difference between V4 and DE+AT disappeared. The causes of this convergence cannot be unequivocally determined based on the GET test; they may reflect both the higher emission intensity of some DE+AT regions and historically higher fossil fuel consumption in some V4 regions, such as Poland or the Czech Republic. Environmental adjustment thus leads to the statistical indistinguishability of the two groups in terms of planetary pressures adjusted human development, and an explanation of this phenomenon warrants further analysis.

Figure 8: GET Test: R-PHDI-A, V4 vs. DE+AT, NUTS 2 Regions, 2000–2024 (p = 0,487)



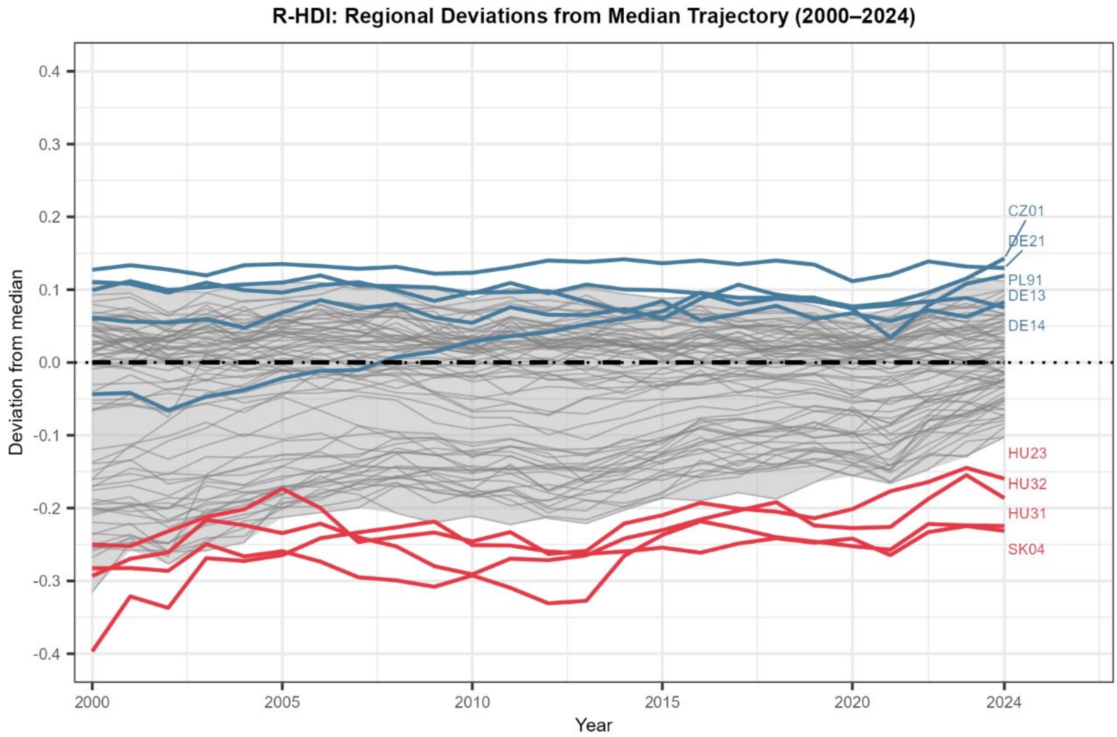
Source: Authors' own calculations based on Eurostat and EDGAR data

Note: Dashed line = central function (functional median, ERL depth method); shaded area = 95% simultaneous confidence envelope based on 999 permutations; red line with points = observed mean curve (data function).

4.5.2. Impact of Environmental Adjustment on Regional R-HDI Values

The third part of the FDA analysis focuses on identifying regional deviations and extreme trajectories through the visualisation of difference curves. Unlike the previous sections, where groups of regions were compared, here each region is assessed individually against the distribution of all 84 pilot regions. For each index analysed, the deviation of the regional curve from the median trajectory was calculated, with the 90 % central area (grey area) defining the interval within which 90 % of the regional curves with the highest functional depth according to the ERL method fall. Regions whose trajectories lie outside this envelope are designated as functional outliers: in blue, regions that are consistently above average; in red, regions that are consistently below average. This analysis was carried out from three different perspectives: the absolute position of regions in the R-HDI, the gender gap as the difference between R-HDI (M) and R-HDI (F), and environmental penalisation expressed as the difference between R-HDI and R-PHDI-A.

Figure 9: R-HDI Difference Curves and Outliers, NUTS 2 (DE, AT, V4), 2000–2024



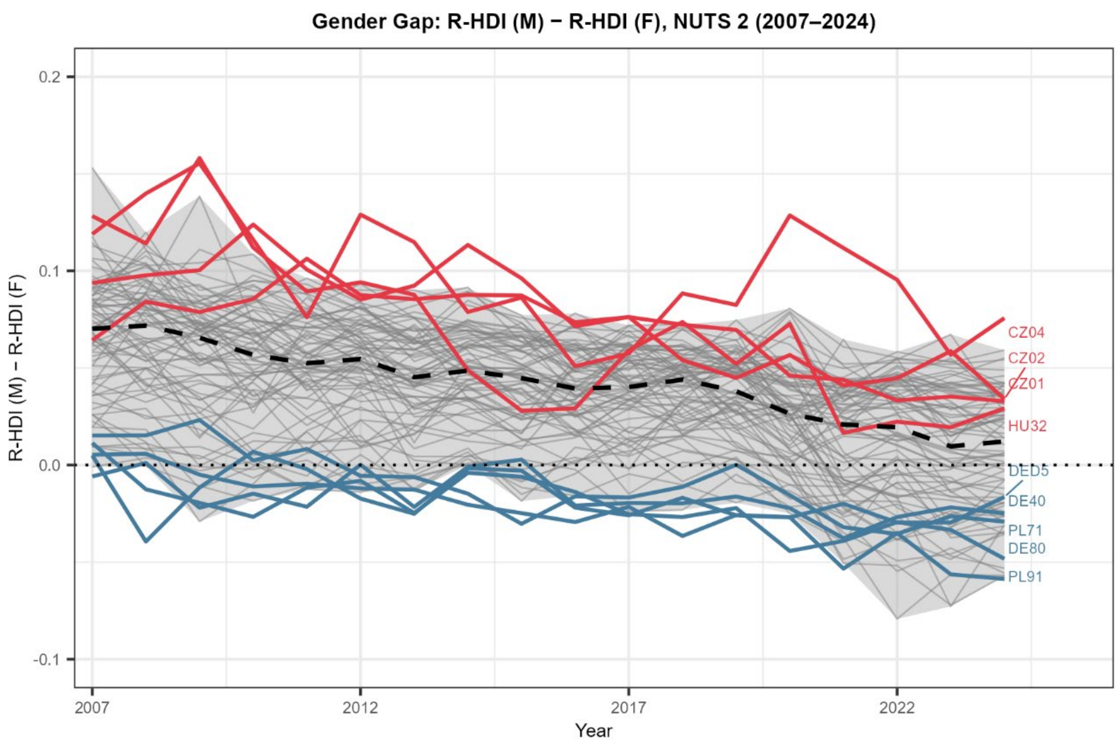
Source: Authors' own calculations based on Eurostat data.

Note: Dashed line = zero deviation (median trajectory); shaded area = 90 % central region (ERL depth method); blue lines = regions persistently above the envelope (high outliers); red lines = regions persistently below the envelope (low outliers). Region labels are shown for 2024.

Figure 9 shows the deviations of individual regional R-HDI curves from the median trajectory of the entire pilot sample for the period 2000–2024. The dotted line represents zero deviation (median trajectory), and the grey area delineates the 90 % central region. Regions that are consistently above average, CZ01 (Prague), DE21 (Upper Bavaria), PL91 (Warsaw Capital Region), DE13 (Freiburg), and DE14 (Tübingen), are highlighted in blue, with their trajectories consistently above the envelope throughout the review period.

Regions that are consistently below average, HU23 (Southern Transdanubia), HU31 (Northern Hungary), HU32 (Northern Great Plain), and SK04 (Eastern Slovakia), are shown in red; these remained below the lower boundary of the envelope throughout the period. The results demonstrate the structural polarisation of the pilot sample: above-average regions are predominantly economic centres, whereas below-average regions are located exclusively in Hungary and eastern Slovakia.

Figure 10: R-HDI_F - R-HDI_M Difference Curves and Outliers, NUTS 2 (DE, AT, V4), 2007–2024



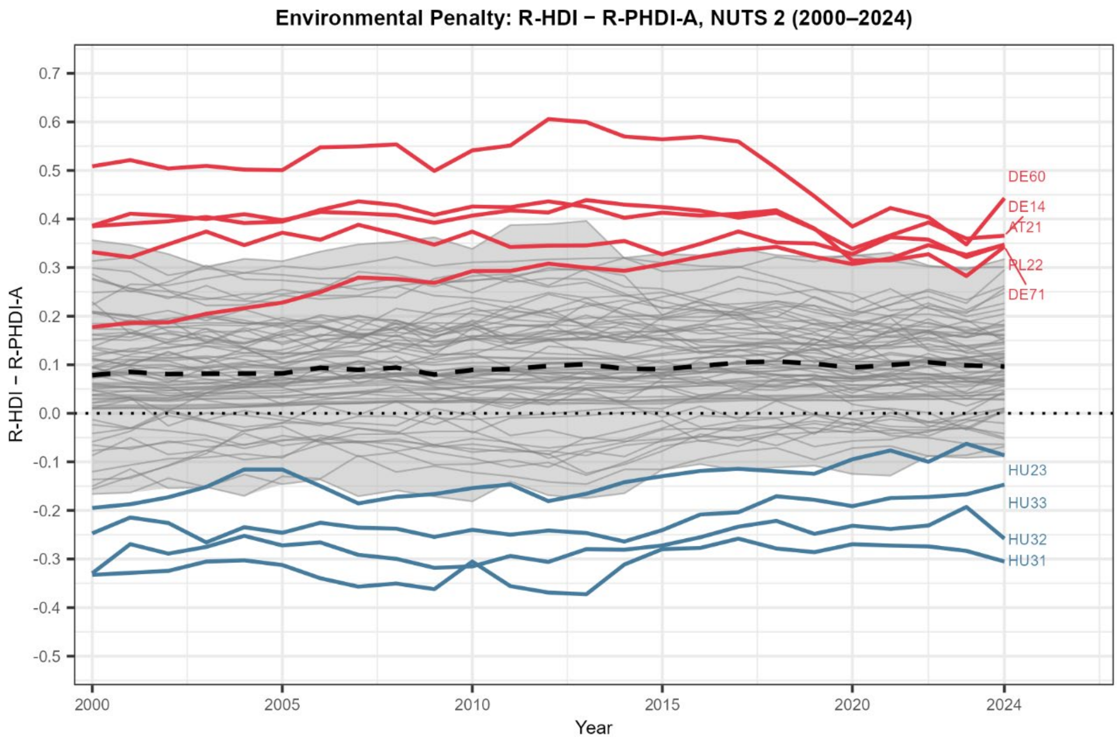
Source: Authors' own calculations based on Eurostat data.

Note: Dashed line = zero deviation (median trajectory); shaded area = 90 % central region (ERL depth method); blue lines = regions persistently above the envelope (high outliers); red lines = regions persistently below the envelope (low outliers). Region labels are shown for 2024.

Figure 10 shows the gender gap in the R-HDI, defined as the difference R-HDI (M) − R-HDI (F) for each region over the period 2007–2024. Positive values indicate a higher male HDI, whereas negative values indicate a higher female HDI. The dotted line represents the median trajectory of the gender gap, and the grey area delineates the 90 % central region. Regions with a consistently above-average gender gap in favour of men, CZ04 (North-West), CZ02 (Central Bohemia), CZ01 (Prague), and HU32 (Northern Great Plain), are highlighted in red; their trajectories lie consistently above the upper boundary of the envelope.

Regions where the female HDI consistently exceeds the male HDI are shown in blue, DED5 (Leipzig), DE40 (Brandenburg), PL71 (Łódzkie), DE80 (Mecklenburg-Vorpommern) and PL91 (Warszawski stołeczny). An important finding is the marked downward trend in the median curve; the gender gap is systematically narrowing in all regions of the pilot sample, with some regions shifting from positive to negative values, that is, from a state of male HDI dominance to one of female HDI dominance.

Figure 11: R-HDI − R-PHDI-A Difference Curves and Outliers, NUTS 2 (DE, AT, V4), 2000–2024



Source: Authors' own calculations based on Eurostat data.

Note: Dashed line = zero deviation (median trajectory); shaded area = 90 % central region (ERL depth method); blue lines = regions persistently above the envelope (high outliers); red lines = regions persistently below the envelope (low outliers). Region labels shown in 2024

Figure 11 shows the environmental penalisation defined as the difference R-HDI − R-PHDI-A for each region over the period 2000–2024. Positive values indicate regions where environmental adjustment for greenhouse gas emissions reduces the index value, that is, regions penalised for high emissions. Conversely, negative values indicate regions whose low emissions lead to an improvement in their relative position compared to the average. The dotted line represents the median penalisation trajectory, and the grey area delineates the 90 % confidence interval.

Regions with consistently above-average penalties are highlighted in red, such as DE60 (Hamburg), DE14 (Tübingen), AT21 (Carinthia), PL22 (Silesia), and DE71 (Darmstadt), whose high emissions of an industrial or energy-related nature led to a systematic reduction in the index after adjustment. The regions HU31 (Northern Hungary), HU32 (Northern Great Plain), HU33 (Southern Great Plain), and HU23 (Southern Transdanubia) are shown in blue. The median penalty increases slightly over time, from approximately 0,08 in 2000 to 0,10 in 2024, reflecting the growing divergence between emission-intensive and low-emission regions.

All FDA analyses, including graphical visualisation, were performed in the R environment version 4.5.2 (R Core Team, 2025) within the Positron IDE (Posit, PBC, 2024) using the GET version 1.0.7 (Myllymäki, Mrkvička, 2023) and ggplot2 (Wickham, 2016) packages. An example of the R script is provided in Appendix B

4.6. Evaluation of Research Questions and Hypotheses

The results presented in Chapter 4.3–4.5 provide an empirical basis for evaluating the four hypotheses. Table 11 summarises the evaluation of each hypothesis with reference to the relevant results.

Table 11: Evaluation of Research Hypotheses

Hypothesis	Key evidence	Result
H1: The HDI family is the most suitable basis for regional sustainability assessment at NUTS 2	Chapter 4.1 (assessment of indicator families); Chapter 4.2 (methodological comparison of candidate families)	Confirmed
H2: Data availability is sufficient for R-HDI and R-PHDI at NUTS 2 for at least three programming periods; R-IHDI and R-GDI require methodological compromises	Tables 7, 8; Chapter 4.3; R-IHDI limitation (Chapter 4.5.1)	Confirmed
H3: Adjusted HDI variants show different regional patterns than R-HDI; R-PHDI identifies high-emission industrial regions as problematic	Figures 6, 9–11 (different regional patterns and environmental penalisation); Table 10; Chapter 4.5.1	Confirmed
H4: Regional development trajectories differ significantly between V4 and DE+AT; convergence depends on the index variant	Figures 7–8; Table 10; p = 0,001 (R-HDI) vs. p = 0,487 (R-PHDI-A); Chapter 4.5.2 and 4.5.3	Confirmed

Source: Authors' own elaboration.

5. Discussion

The discussion is structured in accordance with the logic of the research questions and corresponding hypotheses. First, the choice of the HDI family as the main analytical tool is justified, and the role of alternative approaches within a broader evaluation framework is defined. Subsequently, the availability of data for the individual index variants and the suitability of the NUTS levels for various types of sustainability analyses were critically assessed. The third section interprets the results of the pilot application, including environmental adjustments. The concluding analytical section discusses the results of the functional data analysis and their implications for evaluating the effectiveness of the EU cohesion policy. The chapter concludes with a summary of the study limitations and suggestions for further research.

5.1. Selection of the HDI family and the role of alternative approaches (RQ1/H1)

The results of the evaluation matrix (4.1) and the methodological comparison (4.2) unequivocally confirm H1: in terms of methodological consistency, institutional anchoring, and data availability, the HDI family represents the most suitable basis for regional sustainability assessment at the NUTS 2 level in the EU context. From a methodological perspective, it is the only one of the four candidate families to meet all the criteria of the Nardo et al. (2008) standard: min-max normalisation, a geometric mean preventing full substitution of dimensions, and systematic technical documentation. From an institutional perspective, it is the only one to have two systematic subnational applications covering EU NUTS 2 (Hardeman, Dijkstra, 2014; Smits, Permanyer, 2019), with the R-HDI having been developed directly at the request of the European Commission. From a paradigmatic perspective, the PHDI, as an operationalisation of the interconnection between the social foundation and the ecological ceiling (Hickel, 2020), corresponds to medium-strength sustainability (Neumayer, 2013), consistent with the objectives of the Green Deal (European Commission, 2019).

Alternative families are methodologically relevant but are otherwise limited in terms of the needs of this study. The SDG Index offers the broadest coverage of dimensions, but the 126 sub-indicators present an insurmountable barrier to data availability at the NUTS 2 level. The Ecological Footprint provides a robust measure of the environmental dimension but lacks a social and economic component and has no systematic application at the EU regional level. The GPI/ISEW, as the only family alongside the HDI covering all three dimensions in parallel, suffers from high methodological heterogeneity and the absence of an overarching institution to ensure standardisation. Therefore, these three families serve as a reference framework for interpreting the results of this study, and their systematic integration into a unified analytical framework for assessing regional sustainability is the subject of further research.

5.2. Data Availability and Suitability of NUTS Levels (RQ2/H2)

The empirical analysis of data availability (Chapter 4.3) confirms H2 with an important qualification. The R-HDI and R-PHDI-A are fully feasible at NUTS 2 level for four programming periods in accordance with the R-HDI methodology (Hardeman, Dijkstra, 2014), with the total proportion of missing values not exceeding 10,4 % (Table 8). R-PHDI-B, on the other hand, is purely a model-based measure — the material footprint approximated from national material flow data (Eurostat, 2026b) disaggregated by industrial employment weights (sectors B–F) is only available from 2015 onwards, and its regional disaggregation represents a rough approximation without a direct empirical basis at the NUTS 2 level. Therefore, it serves solely to illustrate the index's sensitivity to the choice of environmental indicators rather than as a standalone analytical result.

The R-IHDI and R-GDI are only feasible with methodological trade-offs. In the case of the R-IHDI, without microdata on the distribution of income, education and health within regions, the Atkinson inequality index cannot be calculated in full accordance with the UNDP methodology (2024). The R-IHDI results therefore reflect inter-regional disparities rather than actual intra-population inequalities — a limitation already identified by Hardeman and Dijkstra (2014) in the context of the R-HDI — and should be treated as an illustration of methodological limitations rather than as a fully-fledged result. In the case of the R-GDI, R-HDI_F, and R-HDI_M, the derived incomes by gender (HHInc_F, HHInc_M) represent modelled data approximated from the national level using the shares of the economically active population (Eurostat, 2026b) and the gender pay gap. Therefore, these results capture relative gender differences and their evolution over time more reliably than the absolute income levels of individual genders.

However, a major caveat to the confirmation of H2 remains the fact that some regions have no or only minimal data of their own for certain indicators, particularly HHInc in German regions at the start of the period under review. Consequently, the Amelia II multiple imputation method (Honaker, King, Blackwell, 2011) was not used, as it assumes that missing values are random (MAR) and requires a dense dataset as input for the EM algorithm — conditions that structural data gaps do not meet. Instead, three methods were applied that explicitly acknowledge the approximate nature of the result: direct imputation from a higher-level administrative unit for regions without their own data; a proportional method preserving the region's longitudinal relationship with its parent unit for longer systematic gaps; and linear interpolation for short gaps not exceeding three years, which preserves the time series trend without introducing information from other regions.

An analysis of developments in the NUTS classification (Chapter 4.3.1) identifies changes in Germany prior to 2007 and in Hungary and Poland during the period 2013–2016 as significant discontinuities. The Czech Republic and Slovakia show a completely stable NUTS 2 structure throughout the entire period under review without any changes. Austria recorded minor administrative adjustments but without any change to the basic regional structure that would affect data consistency. Although the impacts of the identified discontinuities were addressed by direct recalculation from a higher territorial level, residual discontinuities in Eurostat's source data cannot be ruled out; these may manifest as apparent jumps in time series unrelated to the region's actual development.

5.3. Results of the pilot application and environmental adjustments (RQ3/H3)

The results of the pilot application confirm H3: the adjusted HDI variants reveal regional patterns that the basic R-HDI fails to capture, with the R-PHDI identifying industrial and energy-intensive regions in particular as problematic.

Environmental adjustment via R-PHDI-A fundamentally alters the regional hierarchy. Regions consistently above average in the R-HDI, particularly DE60 Hamburg, DE14 Tübingen, and DE71 Darmstadt, are relatively penalised more than the V4 regions following the adjustment for greenhouse gas emissions, while regions with low emission intensity, such as HU31 Northern Hungary or HU32 Northern Great Plain, improve their relative position. This finding is consistent with the original concept of the PHDI as a tool for revealing the contradiction between high levels of human development and excessive pressure on planetary systems (UNDP, 2020; Hickel, 2020). R-PHDI-B adds the penalising effect of the material footprint beyond the scope of emissions adjustment and further homogenises the distribution of regional values; however, its potential for systematic monitoring is contingent upon the availability of material footprint data directly at the NUTS 2 level, which is currently unavailable. In parallel, the methodological choice between total greenhouse gas emissions converted to CO_2 equivalents, as used in R-PHDI-A, and fossil CO_2 emissions as a narrower but methodologically cleaner alternative with a direct link to the EU's climate commitments (European Commission, 2019) remains an open question for further methodological investigation, with the comparison of Variant A and Variant B in this study serving as a preliminary illustration of this sensitivity.

The gender dimension captured by the R-GDI reveals a downward trend in the gender gap across the entire pilot sample, with some regions shifting from a state of HDI_M dominance to one of HDI_F dominance — a trend driven primarily by higher education and employment rates among women in regions with a developed tertiary sector, such as DED5 Leipzig or PL91 Warszawski stołeczny. Conversely, the highest gender gap in favour of men persists in the Czech regions CZ04 Severozápad and CZ02 Střední Čechy, where the income dimension remains the dominant source of disparity.

5.4. FDA results and implications for EU cohesion policy (RQ4/H4)

Functional boxplots (Chapter 4.5.1) capture the overall dynamics of regional development in the pilot sample as continuous trajectories over time — an approach that allows for the identification of patterns differing not in value but in the shape of development (Ramsay, Silverman, 2005). Systematically lower R-IHDI values compared to R-HDI illustrate the methodological limitations of calculations without microdata, while the downward trend in the R-GDI gender gap and the comparison of R-HDI_F and R-HDI_M demonstrate the gradual levelling of opportunities for women and men across the pilot sample.

The results of the global envelope test (Chapter 4.5.2) confirm H4: the trajectory of regional development as measured by the R-HDI differs statistically significantly between the V4 and DE+AT groups throughout the entire period under review, 2000–2024 ($p = 0{,}001$), with the observed average curve lying outside the 95 % simultaneous confidence envelope at all 25 time points for both groups. The fundamentally different result of the GET test for R-PHDI-A ($p = 0{,}487$) shows that, following environmental adjustment for greenhouse gas emissions, the statistically significant difference between the two groups disappears. The causes of this statistical convergence cannot be clearly determined; they may reflect both the higher emission intensity of some DE+AT regions and historically higher fossil fuel consumption in some V4 regions. The GET test thus allows us to formally verify that the choice of indicator fundamentally influences conclusions about convergence, an approach that classical cross-sectional methods do not permit (Myllymäki, Mrkvička, 2023).

The analysis of difference curves (Chapter 4.5.3) extends group comparisons to include an individual perspective and identifies regions that are structural outliers. Consistently above-average regions, such as CZ01 Prague or PL91 Warsaw Capital Region, represent a typical model of metropolitan centres with dynamic HDI growth, while consistently below-average regions, such as HU31 Northern Hungary or SK04 Eastern Slovakia, demonstrate persistent structural underdevelopment. A comparison of environmental penalties across indices revealed that regions with the highest R-HDI were not identical to those with the highest environmental burden. For example, DE60 Hamburg or PL22 Śląskie are heavily penalised for emissions, whereas Hungarian regions improve their relative position after adjustment. Functional outlier analysis thus naturally complements group tests by identifying specific regions, and in follow-up research, this approach can be extended to include functional clustering, enabling a systematic typology of development trajectories across all EU27 regions (Myllymäki, Mrkvička, 2023).

The results of the pilot application suggest that the family of regional HDI variants can play a useful complementary role in the EU cohesion policy evaluation system. The R-HDI offers a multidimensional alternative to GDP per capita as a criterion for regional eligibility for support from the Structural Funds, while the R-PHDI allows the environmental dimension of development to be considered when assessing the impacts of investments financed by the Cohesion Funds. The FDA with GET tests provides a methodological framework for the formal statistical verification of convergence hypotheses across programming periods — precisely the type of analysis that the evaluation of EU cohesion policy typically requires (European Union, 2003).

5.5. Limitations of the study and directions for further research

The present study had several important limitations. The pilot application is geographically limited to six Central European countries, the V4 group (the Czech Republic, Slovakia, Hungary, and Poland), and DE+AT as a reference group of the original EU Member States; therefore, its results cannot be generalised to the entire EU area without further verification. The time coverage of 2000–2024 was determined by the availability of source data in Eurostat and EDGAR, with missing values being imputed using methods based on information from higher-level regional units or an interpolation method. The R-IHDI represents an attempt to translate the inequality index from the national to the NUTS 2 regional level; however, its values capture inter-regional disparity rather than intra-population inequality and should be interpreted as a simulation of the IHDI. Functional data analysis was applied in this study. GET tests and functional boxplots serve to illustrate the methodological potential of the approach on a pilot dataset rather than as an exhaustive analytical result.

The identified limitations also provide directions for future research. The most natural extension is the application of the derived methodology to all EU27 regions, which will enable a systematic comparison of development trajectories across the entire cohesion policy area and the verification of the robustness of the findings presented here. It should be noted that the dynamic goalposts are sample-dependent; extending the analysis to all EU27 regions would alter the normalisation bounds and the absolute index values. In the field of FDA methods, functional clustering, which identifies natural groups of regions based on the shape of their trajectories without predefined groups, represents a natural extension of the GET tests applied here, particularly when applied to the entire EU27. From the perspective of indicator construction, open questions remain regarding the availability of material footprint data directly at the NUTS 2 level for a full-fledged R-PHDI-B, microdata for calculating the Atkinson index of inequality within regions for a full-fledged R-IHDI, and the choice between total GHG emissions and fossil CO_2 emissions in the R-PHDI adjustment factor. Finally, given the nature of the links between the HDI family of indicators and GDP, a systematic assessment of the relationship between the R-HDI and its variants and GDP per capita at the NUTS 2 level remains an open analytical question. Another avenue for research is a systematic comparison of the R-HDI family with alternative regional indicators available at the NUTS 2 level, in particular the EU-SPI (De Dominicis et al., 2024) as a systematic elaboration of the social dimension with proven institutional anchoring in EU cohesion policy.

6. Conclusions

This study contributes to the debate on measuring regional sustainability in the EU in two main ways. First, by systematically assessing families of sustainability indicators in terms of methodological soundness, data availability, and territorial applicability at the NUTS 2 level, it identifies the HDI family as the most suitable basis for regional sustainability analysis in the context of EU cohesion policy. Second, through a pilot application to a sample of 84 regions across six Central European countries for the period 2000–2024, it presents a novel application of regional HDI variants, combined with environmental adjustment and functional data analysis, at the NUTS 2 level in the EU. The results of functional data analysis using global envelope tests demonstrate that the choice of indicator fundamentally influences conclusions regarding regional convergence — the socio-economic convergence of the V4 towards DE+AT, evident when measured by the R-HDI, statistically disappears following environmental adjustment via the R-PHDI. Follow-up research should focus on extending the application to all EU27 regions, functional clustering of regional development trajectories, and systematic assessment of the relationship between HDI variants and GDP per capita at the NUTS 2 level.

From a policy-making perspective, the results support the argument for a fundamental re-evaluation of the criteria for assessing regional development in the EU. The ongoing effort to supplement or replace GDP per capita with multidimensional indicators that capture the social, economic and environmental dimensions simultaneously, in line with post-growth approaches and the wellbeing orientation of European policies, represents not only a methodological improvement but also an important prerequisite for a cohesion policy capable of responding to the challenges of the polycrisis; this study contributes a methodological step in this direction.

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8. List of Indicators Abbreviations

ANS	Adjusted Net Savings
BLI	Better Life Index
CCPI	Climate Change Performance Index
CF	Carbon Footprint
DPSIR	Drivers-Pressure-State-Impact-Response
EDGAR	Emissions Database for Global Atmospheric Research
EF	Ecological Footprint
EPI	Environmental Performance Index
ESI	Environmental Sustainability Index
EVI	Environmental Vulnerability Index
GDI	Gender Development Index
GDP	Gross Domestic Product
GHG	Greenhouse Gases
GII	Gender Inequality Index
GNH	Gross National Happiness
GNI	Gross National Income

GPI	Genuine Progress Indicator
HDI	Human Development Index
HPI	Happy Planet Index
IHDI	Inequality-adjusted Human Development Index
ISEW	Index of Sustainable Economic Welfare
IWI	Inclusive Wealth Index
LF	Land Footprint
LPI	Living Planet Index
MDGs	Millennium Development Goals
MEW	Measure of Economic Welfare
MF	Material Footprint
MPI	Multidimensional Poverty Index
NEET	Not in Employment, Education or Training
PHDI	Planetary Pressures-adjusted Human Development Index
PPP	Purchasing Power Parity
PSR	Pressure-State-Response
R-GDI	Regional Gender Development Index
R-HDI	Regional Human Development Index
R-IHDI	Regional Inequality-adjusted Human Development Index
R-PHDI	Regional Planetary Pressures-adjusted Human Development Index
SDG	Sustainable Development Goals
SEEA	System of Environmental-Economic Accounting
SHDI	Subnational Human Development Index
SPI	Social Progress Index
SWB	Subjective Well-being
WF	Water Footprint
WHR	World Happiness Report
WISE	Wellbeing, Inclusion, Sustainability

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10. Appendix A: Descriptive Statistics of the R-HDI Index Family

Table A1: Descriptive Statistics of the R-HDI Index Family, NUTS 2 Regions (DE, AT, V4)

Period	n	Min	Mean	Median	Max	SD
R-HDI						
2000–2004	420	0,058	0,412	0,463	0,605	0,119
2005–2009	420	0,209	0,458	0,509	0,658	0,108
2010–2014	420	0,237	0,524	0,562	0,726	0,105
2015–2019	420	0,328	0,577	0,603	0,761	0,088
2020–2024	420	0,362	0,614	0,632	0,780	0,079
R-IHDI						
2000–2004	420	0,053	0,387	0,434	0,577	0,112
2005–2009	420	0,200	0,458	0,490	0,639	0,101
2010–2014	420	0,230	0,515	0,546	0,650	0,102
2015–2019	420	0,322	0,568	0,593	0,751	0,087
2020–2024	420	0,357	0,607	0,625	0,772	0,078
R-HDI (F)						
2007–2011	420	0,061	0,410	0,444	0,579	0,101
2012–2016	420	0,155	0,461	0,498	0,615	0,094
2017–2021	420	0,304	0,512	0,533	0,656	0,075
2022–2024	252	0,341	0,556	0,561	0,710	0,062
R-HDI (M)						
2007–2011	420	0,178	0,468	0,501	0,642	0,099
2012–2016	420	0,197	0,504	0,534	0,684	0,096
2017–2021	420	0,301	0,541	0,565	0,704	0,077
2022–2024	252	0,307	0,566	0,579	0,716	0,071
R-PHDI-A						
2000–2004	420	0,000	0,324	0,352	0,524	0,121
2005–2009	420	0,014	0,378	0,395	0,588	0,120
2010–2014	420	0,014	0,423	0,439	0,650	0,123
2015–2019	420	0,082	0,471	0,484	0,687	0,115
2020–2024	420	0,166	0,514	0,529	0,754	0,106
R-PHDI-B						
2015–2019	420	0,094	0,450	0,460	0,685	0,112
2020–2023	336	0,094	0,487	0,495	0,732	0,107

Source: Authors' own calculations based on Eurostat and EDGAR data.

Note: n = number of region-year observations (84 regions × number of years in the period). The functional median corresponds to the curve with the highest ERL depth. R-HDI (F) and R-HDI (M) available from 2007; R-PHDI-B available from 2015.

11. Appendix B: Functional Data Analysis in R — Illustrated Example

This appendix provides a concise illustration of the functional data analysis (FDA) workflow implemented in this study using the GET package (Myllymäki, Mrkvička, 2023) in R.

```
# 04_FDA_GET_test.R
# Global Envelope Test — R-HDI and R-PHDI-A: V4 vs. DE+AT
# EWP: Measuring Regional Sustainability in the EU # Author: Antonín Hořčica
# ---------------------------------------------------------
```

Step 1 — Prepare the curve set:

```
library(tidyverse)
library(readxl)
library(GET)

# Load data and reshape to wide format
dat <- read_excel("analysis/RHDI_analysis.xlsx",
                  sheet = "RHDI_long") |>
  pivot_wider(names_from = code, values_from = RHDI) |>
  arrange(year)

# Create curve set object (rows = time points, columns = regions)
cs <- curve_set(list(
  r   = as.numeric(dat$year),
  obs = as.matrix(dat[ , -1])
))
```

Step 2 — Functional boxplot:

```
# Compute 50 % central region (functional analogue of interquartile range)
cr50 <- central_region(cs, coverage = 0.50)
plot(cr50)
```

Step 3 — Global envelope test (two groups):

```
# Assign regions to groups
groups <- factor(
  ifelse(substr(colnames(cs$obs), 1, 2) %in%
         c("CZ","SK","HU","PL"), "V4", "DE+AT")
)

# Permutation-based GET test
res <- global_envelope_test(cs, type = "erl", groups = groups)
plot(res)
attr(res, "p_interval")
```

The resulting plot displays the difference curve (V4 − DE+AT) with a simultaneous confidence envelope. If the envelope does not contain zero for any time point, the null hypothesis of identical trajectories is rejected at the given significance level.

12. Appendix C: Computational Details — Regional HDI Variants and Data Preparation

C1 Calculation of Regional HDI

The R-HDI represents the basic variant of the regional Human Development Index, calculated from sub-indicators available in Eurostat and covering three dimensions: health, education and income. The remaining three variants (R-IHDI, R-GDI, R-PHDI) extend this basic model with additional dimensions: inequality, gender and environmental pressure. All four variants share the same mathematical core — min-max normalisation and the geometric mean as the aggregation method — and differ only in their supplementary adjustments. The specific sub-indicators and their data sources are listed in Table 5.

The R-HDI itself is calculated in accordance with the R-HDI methodology (Hardeman, Dijkstra, 2014) and UNDP Technical Notes (UNDP, 2024) in five steps. First, for each of the six sub-indicators (life expectancy, infant mortality, NEET, tertiary education, net income, employment), **dynamic goalposts** — minimum and maximum values — are determined from the observed values across all 84 regions of DE+AT+V4 for the entire period 2000–2024. The sub-indicators are then normalised using **a min-max transformation**: for an indicator with a positive trend:

$$x_n = (x - \min) / (\max - \min) \qquad (1)$$

For an indicator with a negative trend, the inverse procedure is applied. In the third step, **three-dimensional indices** are calculated as the average of the normalised sub-indicators:

I_{health} = (life expectancy + inverse infant mortality) / 2;

$I_{education}$ = (inverse NEET + tertiary education) /2;

I_{income} = (net income + employment) / 2 (2)

Finally, **the R-HDI** is **calculated as the geometric mean of** the three dimensions:

$$\text{R-HDI} = \sqrt[3]{(I_{health} \times I_{education} \times I_{income})} \qquad (3)$$

thereby ensuring that a low value in one dimension cannot be offset by a high value in another. The methodology differs from the UNDP standard only in the choice of sub-indicators (adapted to availability in Eurostat) and dynamic goalposts (derived from European regional data rather than global boundaries), thereby preserving the index's sensitivity to detecting intra-European disparities.

The R-IHDI extends the R-HDI by adjusting for inequality using the Atkinson index, calculated from the distribution of dimensional indices across regions for each year — thereby capturing inter-regional disparity. The R-GDI introduces gender disaggregation of all three dimensions; income by gender is derived from data on employment and the gender pay gap available at NUTS 0 level. The R-PHDI adds a planetary pressure adjustment factor constructed from greenhouse gas emissions (Variant A, EDGAR) or a combination of these with the material footprint (Variant B).

C2 Detailed Calculation of Regional HDI Variants

The R-IHDI extends the R-HDI by **adjusting for inequality** calculated using the Atkinson inequality index according to UNDP (2024). For each of the three dimensions, the Atkinson index *A* is calculated from the distribution of the dimensional indices, measuring the degree of inequality in the distribution of health, education and income within the population of each region. The Atkinson index for each dimension is calculated as:

$A = 1 - (\mu_g / \mu)$ (4)

where μ_g is the geometric mean and μ is the arithmetic mean of the indicator in the region. The dimensional indices are then adjusted for this inequality:

adjusted $I_{dim} = I_{dim} \times (1 - A)$ (5)

thereby resulting in a lower index value in regions with higher internal inequality. The R-IHDI is then calculated using the same geometric mean as the R-HDI, but from the already adjusted dimensional indices.

The R-GDI introduces **gender disaggregation** for all three dimensions, in line with UNDP (2024). For the health and education dimensions, sub-indicators are calculated separately for women and men based on gender-disaggregated data from the LFS and Eurostat. For the income dimension, female/male estimated earned income is used, based on a combination of data on employment and income. The R-GDI is then calculated as the geometric mean of these gender-specific dimensions, thereby capturing gender disparities in human development.

The R-PHDI includes **an adjustment for planetary pressure** according to UNDP (2020), which integrates the environmental dimension into the human development framework. The adjustment factor is constructed from indicators measuring a given region's pressure on planetary systems. In the pilot application of this article, **two variants** are tested to assess the index's sensitivity to the choice of environmental indicators.

Variant A (one-dimensional) uses total GHG **emissions per capita** (from the EDGAR database), which are available at NUTS 2 level without approximations. The adjustment factor is calculated as min-max normalisation:

$AF_A = (E_{GHG\_max} - E_{GHG}) / (E_{GHG\_max} - E_{GHG\_min})$ (6)

where E_{GHG} are total GHG emissions per capita (CO_2eq) in the region and E_{GHG_max} and E_{GHG_min} are the maximum and minimum values across all regions and years 2000–2028 (including a five-year linear projection from 2023).

R-PHDI Variant A is then:

$R\text{-}PHDI_A = R\text{-}HDI \times AF_A$ (7)

Variant B (two-dimensional) extends the model to include **the material footprint per capita** (*MF*), approximated from national material accounting data disaggregated to the regional level using industrial employment weights (sectors B–F). The adjustment factor is calculated as the arithmetic mean of two min-max normalised components:

$AF_B = (CO_{2\_norm} + MF_{norm}) / 2$ (8)

where CO_2_norm = (CO_2_max − CO_2) / (CO_2_max − CO_2_min) and MF_norm = (MF_max − MF) / (MF_max − MF_min), with min and max values derived from the observed period 2015–2023.

R-PHDI Variant B is then:

R-PHDI_B = R-HDI × AF_B (9)

Both approaches reduce the R-HDI value in regions with excessive emissions, with Variant B capturing a broader spectrum of environmental pressure. A comparison of both versions using DE+AT+V4 data is the subject of Chapter 4.5, where differences in spatial patterns and sensitivity to the choice of environmental indicators are discussed.

C3 Derivation of Approximated Sub-indicators

Infant mortality by sex (InfMort_F, InfMort_M) is not available at NUTS 2 level in Eurostat. It was estimated using the total regional InfMort value and the national sex ratio derived from the demo_minfs database (NUTS 0):

$$InfMort\_F_{r,t} = InfMort_{r,t} \cdot \frac{InfMort\_F_{n,t}}{InfMort_{n,t}} \quad (10)$$

where r denotes the NUTS 2 region, n the relevant NUTS 0 country, and t the year. The InfMort_M values were derived in the same way.

Household income by gender (HHInc_F, HHInc_M) is not directly available at NUTS 2 level. They were derived from the total HHInc value at NUTS 2 level, the shares of the economically active population by gender (LabForce_F, LabForce_M from lfst_r_lfp2act) and the gender pay gap (GenderGap from earn_gr_gpgr2, NUTS 0). First, the relative wage ratio of women to men was derived:

$$w_{n,t} = 1 - \frac{GenderGap_{n,t}}{100} \quad (11)$$

The weighted shares of the economically active population were then calculated:

$$s\_F_{r,t} = \frac{EA\_F_{r,t}}{EA\_T_{r,t}} \cdot w_{n,t}, s\_M_{r,t} = \frac{EA\_M_{r,t}}{EA\_T_{r,t}} \quad (12)$$

The incomes of women and men were then derived as:

$$HHInc\_F_{r,t} = HHInc_{r,t} \cdot \frac{s\_F_{r,t}}{s\_F_{r,t} + s\_M_{r,t}} \quad (13)$$

where `$r$ ` denotes the NUTS 2 region, `$n$ ` the relevant NUTS 0 country, and `$t$ ` the year. Values for `HHInc_M` were derived in the same way.

The material flow at NUTS 2 level (MatFlw) is not systematically available in any database. For Variant B R-PHDI, it was derived from national material flow data (env_ac_mfa, NUTS 0) disaggregated using the share of the region's industrial employment (sectors B–F, lfst_r_lfe2en2) in the national total:

$$MatFlw_{r,t} = MatFlw_{n,t} \cdot \frac{EmpBF_{r,t}}{\sum_{r \in n} EmpBF_{r,t}} \quad (14)$$

where$EmpBF_{r,t}$ denotes the number of people employed in industrial sectors B–F in the NUTS 2 region,r the NUTS 2 region,n the relevant NUTS 0 country, and$t$ the year. This approximation is available only for the period 2015–2023 and is reserved for Variant B. Variant A works exclusively with GHG data from the EDGAR database.

All derived variables (InfMort_F, InfMort_M, HHInc_F, HHInc_M, MatFlw) represent modelled data approximated from available higher-level sources. They should therefore be treated with due caution — they indicate trends and relative differences between regions, but cannot replace direct statistical measurements at NUTS 2 level.

C.4 Data Gaps and Imputation Methods by Indicator

Table C1: Data Gaps and Imputation Methods by Indicator — Basic, Female and Male

Indicator	HDI Indicator Group			Data Gap Imputation Method T/F/M		
	Basic (n/%)	Female (n/%)	Male (n/%)	Direct supplements	Proportional method	Linear inter/extrapolation
LifeExp	211/10,0	64/4,2	64/4,2	0/0/0	11/50/52	100/14/12
InfMort	218/10,4	89/5,9	90/6,0	0/0/0	91/0/0	127/3/0
NEET	260/12,4	466/30,8	519/34,3	25/62/151	129/401/368	106/3/0
TerEdu	42/2,0	12/0,8	12/0,8	0/0/0	35/12/12	7/0/0
HHInc	523/24,9	269/17,8	269/17,8	456/0/0	0/0/0	67/269/269
EmpRate	42/2,0	12/0,8	12/0,8	0/0/0	36/12/12	6/0/0
Total	**1296/10,3**	**912/10,1**	**966/10,6**	**481/62/151**	**402/475/444**	**413/375/371**

Source: Author's own calculations based on Eurostat (2026).

Note: n = number of missing values; % = proportion of the total number of values for the given indicator and variant; Female and Male InfMort values were fully derived by calculation (see 4.3.4).

Table C1 shows that the most problematic indicator is HHInc, where approximately a quarter of all values are missing (24,9 % for Basic) — the gaps are concentrated primarily in German regions at the start of the period under review, when data from the nama_10r_2hhinc database were not available for this period. The second critical indicator is NEET, where the proportion of missing values for Female and Male exceeds one-fifth of all values (22,0 % and 21,6 % respectively). The structure of the gaps for the Female and Male variants is very similar and differs only in minor details — a more significant difference occurs only in LifeExp, where the Male variant shows a slightly higher proportion of gaps. The overall proportion of missing values is 10.4 % for Basic, 7,2 % for Female and 6,6 % for Male.