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Are urban areas better environmentally managed than countries?

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Government entities are crucial in implementing effective mitigation and adaptation strategies to cope with climate change. This article introduces an innovative quantitative composite index to assess environmental performance across the city and country levels: a Deterioration of Environmental Performance Index (DEPI). This new index provides valuable and objective insights into the sustainability of territorial development strategies. This article aims to understand how local and national governments address environmental challenges by leveraging these metrics. We compute the annual evolution of DEPI for ten countries from 2001 to 2020. Our findings reveal that, compared to baseline levels, environmentally harmful outcomes generally decrease more significantly (or increase less sharply) over time. In addition, countries tend to outperform their cities in managing five critical environmental impacts: air pollution, river flooding, coastal flooding, forest fires, and heatwaves.

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KEYWORDS

Environmental performance | Urban | Index | Climate change

Executive summary

This article introduces an innovative quantitative composite index to assess environmental performance across the city and country levels: a Deterioration of Environmental Performance Index (DEPI). This new index provides valuable and objective insights into the sustainability of territorial development strategies. In this context, environmental performance for governmental entities primarily reflects the outcomes of policies and human activities that directly or indirectly affect ecosystems. Given the multifaceted nature of environmental challenges, these policies encompass various interventions. This evaluation exclusively incorporates quantitative measures to capture the tangible impacts of human activity. The selected variables are intended to reflect human actions' outcomes and environmental management policies' effectiveness. Some variables are influenced by urban policies, while others by national ones. These variables allow for policy efficiency assessment in managing climate change and human impact across governance levels. The index evaluates two critical dimensions on an annual basis: air quality and climate hazard management. Governments are responsible for safeguarding populations and infrastructure from the adverse effects of global warming. Consequently, the climate hazard dimension encompasses risks like floods, wildfires, and extreme heat. Air pollution is measured by the average population exposure to fine particulate matter (PM2.5). By employing a population-weighted metric, this measure captures individuals' average exposure to PM2.5 across each territory. Each outcome is classified as negative based on its marginal environmental impact. To ensure comparability, calculations are conducted at both local and national levels.

This article examines how local and national governments respond to these environmental challenges. We analyze the annual evolution of the DEPI for ten OECD countries and their respective Functional Urban Areas (FUAs) from 2001 to 2020. The index captures variations in environmental outcomes across multiple governance levels which measures environmental performance evolution. Objective indicators of performance remain relatively scarce for historical analyses. To address this limitation, we construct our index using datasets provided by OECD statistics and assess its robustness through empirical testing.

Our findings show that on average, environmental management is consistently better at the national than at the city level each year. Among the countries in our sample, New Zealand is the only one with poorer national outcomes relative to its urban areas. Further research is needed to unravel the mechanisms that explain these results. Global agreements are insufficient, as they are not reflected in the evolution of quantitative outcomes. Environmental policies still need to be applied at all levels for better effectiveness in mitigating climate change impacts. However, there is a particular need to improve the implementation of local-level policies. Despite establishing ambitious climate plans and mitigation targets, FUAs' performance has deteriorated over time at a greater rate than the environmental performance of their respective countries.

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Introduction

Humans are fundamentally integrated into a global ecosystem, as emphasized by Dasgupta and Treasury (2022). Therefore, household and government decisions are relevant because they have long-lasting implications for this complex ecosystem. A business-as-usual scenario would set off a chain of harmful consequences, extending beyond environmental degradation to disrupt economic and social systems. Due to the intricate interconnectedness of these systems, the deterioration of one area can exacerbate risks in others, triggering a cascading escalation of crises (Von Uexkull & Buhaug, 2021; Shi *et al.*, 2019; Matsumoto *et al.*, 2019; Aminzadeh, 2006). Historically, a substantial body of research has focused on understanding the environmental impacts of human behavior. However, many scientific recommendations have not been fully integrated into societal actions yet. The responsibility for safeguarding our ecosystem is primarily addressed by associations, governments, international organizations, and non-governmental organizations (NGOs). This can be attributed to the environment's inherent nature as a common good. Additionally, the lack of short-term profitability may discourage proactive engagement from the private sector (Schneider, 2014). Nevertheless, recent years have shown some progress in this area. A comprehensive ecological transformation of the global economy is essential. This requires transitioning from environmentally harmful production and consumption processes to sustainable alternatives across all economic sectors to mitigate the impact of human activities on our planet. In this context, we focus on governmental bodies, as they are entrusted with serving the public interest and possess greater capacity for effective action due to their legislative authority. A nation's economic identity represents a complex, interconnected matrix of numerous factors, such as market systems, trade routes, natural resources, and population distribution. It extends beyond being a simple assembly of cities. However, cities are hubs of economic dynamism and play a vital role in shaping the economic power of a nation. Economic output from the largest metropolitan regions is frequently like that of significant nations. For instance, the economic production of Tokyo can be compared to the entire global domestic product (GDP) of South Korea (Matsumoto *et al.*, 2019).

In parallel, a nation's environmental performance is not a simple aggregation of urban areas. It is a sophisticated interplay among cities, rural spaces, and adherence to policies enforced at different levels. Hence, data at the local and national levels are examined and compared for a comprehensive understanding of a nation's environmental performance (Eisenack & Roggero, 2022). Furthermore, Matsumoto *et al.* (2019) highlighted the capacity and relevance of local scale to address climate change in their OECD report, "An Integrated Approach to the Paris Climate Agreement: The Role of Regions and Cities". With more than half the global population, cities generate 80% of the worldwide GDP and contribute significantly to greenhouse gas (GHG) emissions, generating more than 70% of energy-related CO_2 emissions. Urban ways of life, such as transportation methods and energy use at home, are significant determinants of GHG emissions. Projections suggest that if current trends persist, global urban primary energy use and CO_2 emissions could increase by 70% and 50% by 2050 from their 2013 levels. The impact of climate change also poses a severe threat to cities, especially those in low-lying coastal regions, which are exposed to an increasing risk of flooding. Current estimations predict that global flood losses in the world's largest coastal cities could reach 52 billion USD by 2050 (Matsumoto *et al.*, 2019). Other climate-change-related phenomena, such as urban heat islands, which increase local temperatures, further intensify the vulnerability of cities. Moreover, they potentially damage infrastructure and increase energy demand for space cooling.

As they face these issues, cities have the potential to mitigate and adapt to climate change. Many climate policies are implemented at the city or regional level. An estimated 50% to 80% of adaptation and mitigation actions are led locally. In many countries, urban municipalities have at least partial authority over various sectors, such as spatial planning, transport, and waste services. This allows them to drive climate action through local regulations and strategic planning. Moreover, technically feasible low-carbon measures can reduce emissions from key urban sectors by almost 90% by 2050. Thus, it would generate substantial savings in the long term. Investments in low-carbon, climate-resilient urban infrastructure can yield additional benefits such as improved health, energy use, and security for a better quality of urban life. For instance, land-use zoning policies promoting higher densities can reduce transport distances, and increasing green spaces can mitigate extreme heat and flooding. Economic growth can also be stimulated through the job creation needed to implement these policies (Matsumoto *et al.*, 2019). Despite the capacity of cities to address climate change-related challenges, their full potential can only be harnessed through effective collaboration with regional and national governments according to the Coalition for Urban Transitions (CUT, 2019). This report underscores the crucial role of national governments in supporting economic growth and mitigating climate change effects through urban transformation. National governments can contribute by financing sustainable urban infrastructure, shaping global agendas, and endorsing city- and community-led climate initiatives. They also play a role in harmonizing national and local policies through comprehensive frameworks such as the Nationally Determined Contributions (NDC) (Matsumoto *et al.*, 2019). Nonetheless, local governments control less than one-third of the potential GHG emissions reduction within their jurisdiction (CUT, 2019). More than two-thirds of the reduction potential depends on national and state governments or coordination across different levels of government. In addition, cities typically have less influence on significant sectors such as energy provision than on areas such as water management, building regulations, waste management, or transportation. This disparity in power distribution might impede the implementation of certain mitigation strategies sought by local governments. Nevertheless, cities have undertaken climate commitments and implemented miscellaneous mitigation and adaptation strategies since the 1990s. These measures range from solar panel installations and building renovations to green space expansion and congestion charges. Moreover, following the Paris Climate Agreement, some cities have set ambitious GHG emission reduction targets that often exceed those of their respective national governments (Matsumoto *et al.*, 2019).

Economics provides a framework for understanding societal behavior and aims to mitigate the inherent uncertainties of our collective future. Within conventional economic models, actors are assumed to behave rationally, making decisions based on resource constraints to achieve the best possible outcome. A key variable in this constraint function is the availability of information. Therefore, it can be argued that optimal environmental outcomes remain unattainable without adequate information and resources. Besides, addressing environmental challenges needs precise quantification and communication of environmental risks, resources, and performance given the widely accepted principle that "effective management requires accurate measurement". Assessing environmental performance is a complex task. It is particularly challenging to encapsulate within a single index, as it involves multiple ecosystem interactions. A composite index appears to be a relevant approach for capturing the multidimensional nature of human activity with ecosystems. In addition, information about a territory's environmental status is generally more accessible and interpretable as a single numerical value with a standardized scale than a set of disparate indices (OECD, 2008). There is no universally accepted definition of a composite index. In this study, we adopt the definition proposed by Greco *et al.*, (2019): "A composite index might reflect a complex system that consists of numerous 'components,' making it easier to understand rather than reducing it to its 'spare parts'". The proliferation of composite indices in recent years reflects the growing need to convey complex, multidimensional realities through simplified and meaningful measures. The increasing number of publications referring to the "composite index" on SCOPUS illustrates this trend. Similarly, as the urgency to address climate change intensifies, the number of environmental indices has surged, each assessing a specific aspect of environmental conditions. The number of SCOPUS results for the "composite environmental index" increased from 10 in June 2001 to 125 in June 2023. However, to our knowledge, no composite index currently exists that quantitatively measures environmental performance at city and national levels. Such an index would facilitate comparisons between different jurisdictional levels, providing a more comprehensive understanding of environmental governance. In this context, this article examines the environmental performance of governmental entities at both city and national levels. We compare these two levels by developing a quantitative composite index (DEPI). We find that urban areas are less effectively managed environmentally than entire nations. Furthermore, by offering additional insights into their respective environmental situations, this research seeks to bridge part of the information gap that may have contributed to suboptimal policy decisions in the past. Given the significant strain on public resources and the escalating climate crisis, ensuring the efficient allocation of these resources is relevant.

This paper is organized as follows. Section 2 briefly reviews existing indices at the city and country levels. Section 3 introduces the framework of the composite index created. Section 4 develops the application scope and explains the treatment applied to the data. The results are presented in Section 5. Finally, Section 6 discusses our results with a robust analysis, and Section 7 concludes.

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Review of environmental performance indices

In this section, we have reviewed widely used environmental indices at the national and city levels. These indices played a significant role in shaping the theoretical and practical concepts of the index proposed in this article.

In a publication from the United Nations Industrial Development Organization, nine city-level sustainability indices were reviewed in 2017. We were particularly interested in the dimensions accounted for in the Green City Index (GCI). This index was first developed in 2008 by the private company the Economist Intelligence Unit in collaboration with Siemens. It is designed to evaluate and rank the environmental performance and aspirations of major cities worldwide. It evaluates cities using approximately 30 indices spread over eight to nine categories, depending on the region, due to data constraints. These categories include CO_2 emissions, energy, buildings, land use, transport, water and sanitation, waste management, air quality, and environmental governance. Sixteen of these indices are quantitative measures, and the other fourteen are qualitative and assess the city's environmental policies. The combination of quantitative and qualitative indices reflects both current environmental performance and its ambitions to become greener. The Green City Index measures *de facto* and *de jure* environmental performance at the urban level (Gong & Lyu, 2017). In contrast to the specific scope of the GCI, footprint-related indices (i.e., environmental, energy, water or final consumption good footprints) can be calculated for various economic actors and levels. Redefining Progress, the Worldwide Fund for Nature and the Global Footprint Network first developed this concept. They provide a comparative measure of human demand versus the planet's ecological capacity regeneration. These indices symbolize the quantity of biologically productive land (i.e., global hectares) needed for resource regeneration and waste neutralization. Regular data and methodological updates have allowed these indices to include more dimensions and reflect scientific advancement since their conception in the 1990s (Gadrey & Jany-Catrice, 2016). Similarly, the net environmental contribution (NEC) assesses the environmental impact of economic activities. The NEC framework is grounded in the concept of sustainable development. It evaluates the extent to which a product, service, company, or sector contributes positively or negatively to the environment. It considers various environmental dimensions, including climate, water, air, biodiversity, and resources. Thus, it offers a holistic perspective of environmental impact. The NEC calculation involves four key steps : (i) to identify the main environmental impact of the product life cycle, service, or sector considered, (ii) to quantify the environmental performance relative to the previously identified environmental impact during the life cycle steps, (iii) to normalize performance by comparing it to the best available technique or practice (a baseline for environmental impact measurements), (iv) and these scores are aggregated to generate a final NEC score. The NEC scores range from -100% to +100%, where negative values indicate net environmental degradation and positive values suggest a net environmental benefit. The global average serves as the NEC 0% point. Scores can also be aggregated for all sectors in a unique range, informing them of impact intensity to compare actors on a single scale. This means that environmental performance is measured as high (-100%/+100%), moderate (-33%/+33%), or limited (-10%/+10%). This index can be applied to various subjects. For example, it can be used by companies to identify areas for improvement and by investors to evaluate the environmental responsibility of their portfolios. However, policymakers can also guide the development of more sustainable regulations (NEC, 2019).

Transitioning to country-level indices, the Environmental Performance Index (EPI), developed by Yale University in 2022, provides a data-driven assessment of national environmental sustainability. It evaluates 180 countries based on 40 performance indicators across 11 issue categories and three policy objectives: climate change management, environmental health, and ecosystem vitality. These indicators collectively measure how closely countries adhere to established international environmental policies. The index is aggregated at multiple levels, with each variable weighed according to its contribution to the total score. The EPI can also be disaggregated by issue category, policy objective, peer group, and country (Wolf *et al.*, 2022). In addition, the Environmental Policy Stringency (EPS) Index, developed by the OECD, assesses the stringency of environmental policies, particularly those addressing climate change and air pollution. The EPS reflects the explicit or implicit cost of environmentally harmful behaviors, with variables selected based on legal regulations encompassing a broad range of policies. Stringency is measured on a 0 to 6 scale, where 0 represents nonexistent policies and 6 indicates the most stringent. The index is calculated using the minimum and maximum sample values of each instrument. He is aggregated first by type of instrument and then by policy approach (market- and non-market-based regulations). The EPS allows for international and historical comparisons covering 28 OECD countries from the 1990s to 2012. It can be further disaggregated by market-based vs. nonmarket-based instruments and by subcomponents such as policies that incentivize or penalize environmental actions (Botta and Koźluk, 2014).

Building on these structured and comprehensive indices, we construct a composite index that captures shifts in environmental outcomes over time. This approach assesses *de facto* environmental performance at local and national levels across multiple dimensions. Importantly, we develop a methodology that facilitates comparisons over time while ensuring the measure remains accessible and easily interpretable for a non-expert audience. The framework is detailed in the following section.

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Theoretical framework

In this section, we present the index proposed in this study. First, we introduce the theoretical concept and incorporate the dimensions. We then discuss the methodology used. The final subsection provides a mathematical illustration.

3.1 Concept and dimensions definition

Environmental performance for governmental entities primarily refers to the outcomes of policies and human activities that directly or indirectly impact the ecosystem. These policies span a wide variety of policies due to the multifaceted nature of environmental concerns. We only include quantitative measures in this evaluation to capture the tangible, 'on-the-ground' effects of human activity. The variables selected are intended to reflect both the outcomes of human activity and the results of environmental management policies. Some variables are more likely to be consequences of local actions, whereas others are more likely to be determined at the national level. Together, they evaluate policy efficiencies to manage climate change and human impact at both levels. Accordingly, our indices assess six key dimensions on an annual basis.

3.1.1 Air quality management

Air pollution is estimated as the mean population exposure to fine particulate matter (PM2.5). “2.5” indicates that particulate matter has a diameter of less than or equal to 2.5 micrometers, approximately 3% of the diameter of a human hair sample. It is calculated considering the population distribution across different areas with varying pollution levels. Hence, as a population-weighted measure, it provides a more accurate representation of individuals' average exposure to PM2.5 within each territory. Research has established a direct causal link between PM2.5 exposure and cardiovascular disease incidence and death rates. Notably, improvements in life expectancy in the United States have been partially attributed to reductions in ambient fine particulate air pollution exposure (Liu *et al.*, 2019). We use total GHG emissions to account for this dimension. As more than 70% of GHG emissions can be attributed to cities, it appears relevant to monitor and compare their efforts to the national level. Moreover, local governments usually have room for urban planning, greatly influencing GHG emissions (Matsumoto *et al.*, 2019).

3.1.2 Climate hazard management

Governments are responsible for protecting their population and infrastructure from the consequences of global warming. Thus, this dimension includes flood, fire, and heat risks. Climate change-induced floods that impact populations and buildings are evaluated as the share of population and built-up area exposed to river and coastal flooding. This accounts for the corresponding human risk, material damage, and water pollution associated with such events. The return period chosen is fifty years. Therefore, in any year, the probability of a flood reaching a similar intensity as a one-in-fifty-year flood is 2%. Due to ecosystem deregulation, important flood events are estimated to increase on all continents over time. A fifty-year return period seems adequate to account for the intensity of such an important environmental catastrophe. However, their frequency might increase. In addition, the engineering benefits of structural measures to improve the capacity of drainage systems are greatest when considering a 50-year return period (Wang *et al.*, 2021). Climate deregulation also involves an increase in fire, partly due to drought and strong winds. Fire risk is no less disastrous than flood risk in terms of human health, material damage, and endangered animals. Moreover, fires instigate a series of subtle and delayed environmental events, including air pollution due to smoke plumes, which eventually contribute to land and water contamination through deposition, toxic runoff water pollution, and additional environmental hazards resulting from the combustion of various materials (Martin *et al.*, 2016). This risk is illustrated by the share of the population exposed to at least one forest fire. Its reduction over time should reflect the government’s efforts to prevent fires and protect people. The increase in temperature and government response is proxied by the share of the population exposed to strong heat stress. Strong heat stress is calculated via the Universal Thermal Climate Index (UTCI) for an equivalent temperature greater than 32 degrees Celsius. The UTCI considers air temperature, wind, radiation, and humidity and assesses the impact of atmospheric conditions on the human body (OECD, n.d.). This kind of temperature can destroy physical and social infrastructures in combination with the effects of extreme storms and drought. Moreover, a temperature rise could increase the demand for space cooling, skyrocketing energy consumption during high demand peaks (Matsumoto *et al.*, 2019).

3.1.3 Community life management

The share of recycled waste of total waste produced by a territory illustrates the effectiveness of policies aimed at waste reduction and recycling. Waste management should improve at every level to limit its impact on our society. Moreover, local entities usually have direct power over waste treatment; thus, they can differentiate among levels (Matsumoto *et al.*, 2019). The availability and network size of public transport for the population are considered via the share of the population living less than 10 minutes from a public transport stop. It is a public measure that can help reduce GHG emissions by encouraging the population to use collective transport rather than personal motorized vehicles. Furthermore, extensive research has conclusively shown that low-density urban areas that lack efficient public transport networks tend to report higher GHG emissions (Matsumoto *et al.*, 2019). Therefore, territories that act to promote and develop their public transport might observe a reduction in GHG emissions over time.

3.1.4 Energy management

This dimension is the share of renewable energy in the energy mix of a given territory, the carbon intensity of energy used, and a measure of energy consumed per capita. Urban development processes and infrastructure play a prominent role in energy use in territories (Larson *et al.,* 2012). Thus, it should be considered by governments at every decision level. Including those metrics in the overall index allows us to follow their evolution and account for territorial efforts to provide efficient and 'greener' energy to its population. The Green City Index also accounts for this dimension using similar measures that are not detailed in their public reports, i.e., renewable energy consumption, energy intensity, and energy consumption.

3.1.5 Natural capital management

The management of green areas and forests is considered based on the ratio between their superficies and those of built-up areas. We also include the share of protected areas in the considered territory. Policies to enhance vegetation and expand green spaces can effectively mitigate the adverse effects of extreme heat and flooding (Matsumoto *et al.*, 2019). Furthermore, evidence strongly supports that proactive implementation in such areas can significantly lower climate change threats to biodiversity (Hannah, 2008). However, there is currently a lack of new protected areas specifically designated for climate change mitigation. By considering this measure, we provide an incentive for policymakers to act.

3.1.6 Water management

This dimension has two outcomes. First, wastewater pollution (measured by the average concentration of hazardous chemicals in natural water[1]) threatens biodiversity and could lead to hazards for human health. This is a prominent issue because freshwater ecosystems have already experienced significant depletion (Albert *et*

[1] e.g., groundwaters, rivers, lakes, and exclusive economic zone sea areas.

al., 2021). Secondly, the responsibility of government entities to mitigate pressure on water resources is included in estimating the water wasted through the leakage rate. Leaks can be reduced by identification, repairs, and investments in network maintenance. These actions can be implemented by local and national governments. This outcome is also accounted for in the NEC framework. The next subsections present a methodology for constructing a new index building upon these previous dimensions and variables.

3.2 Methodology

First, each outcome is classified as positive or negative based on its marginal effect on the environment. For instance, the mean concentration of PM2.5 and population exposure to fire are considered negative, whereas the proportion of protected areas accessible by public transport is positive. The calculations are performed at local and national levels to ensure comparability. Our variables and their respective classifications are presented in Table 1. Next, we compute the annual evolution of each variable using an index with a base 100 as a reference for the analysis period. This approach allows us to account for environmental outcomes independently of their measurement units, facilitating their aggregation. Additionally, the base 100 enables the comparison of values and trends over time, addressing scale discrepancies between national and city-level measures. We then aggregate the variables within each category using a geometric mean. We apply an imperfect substitution method to incorporate strong sustainability into our framework, ensuring that no single dimension can fully compensate for another (Greco *et al.*, 2019; Gadrey & Jany-Catrice, 2016). No weighting is applied, as all outcomes are considered equally important. Moreover, the lack of established theoretical guidance on jointly assessing these outcomes prevents the determination of a robust weighting scheme. At the city level, we account for differences while minimizing information loss. Local-level results require an additional aggregation at the national level. We compute a unique average value across the available locations by applying a simple arithmetic mean to the index results for each country's local components and year. This process yields an average value reflecting the evolution of "negative outcomes" in environmental performance variables at each level and year. Overall categorical DEPI is then derived as the unweighted geometric mean of the base-100 normalized outcomes. This metric enables us to assess whether environmental management is (i) deteriorating, or (ii) improving. Ultimately, it provides insights into the evolution of negative environmental outcomes over time.

3.3 Mathematical definition of DEPI

The DEPI index illustrates changes in environmental outcomes at different levels. Thus, this is an index of environmental performance evolution. Mathematically, the Deterioration of Environmental Performance Index is written as follows:

$$DEPI_{c,TL,t} = \frac{1}{N_{TL}} \times \sum_{n_{TL=1}}^{N_{TL}} \left(\sqrt[N_x]{\prod_{x=1}^{X} \left[\frac{v_{x,c,TL,t}}{v_{x,c,TL,0}} \times 100 \right]} \right) \tag{1}$$

where "x" equals "n" for computing the negative index (i.e., DEPI). Notation is as follows:

- *c*: country.
- *t*: year.
- *TL*: Territorial Level (national or local).
- N_{TL}: number of territorial level (equals 1 for country).
- v_n: variable of marginally negative environmental outcome.
- N_n: number of variables in the "negative" category.

DEPI is compared with a base of 100 used as a reference. A result greater (less) than 100 indicates that outcomes increase (decrease) relative to the baseline level. Environmental performance is better when the DEPI is less than 100, as we evaluate the environmentally harmful outcomes with this index. The next section presents the scope of application of the index.

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Application

This section is structured into four subsections. The first details the data selection process, the next two examine variable selection at local and national levels, and the final subsection discusses the countries included and the calculation period.

4.1 Data Selection

Public data availability poses challenges for assessing the environmental status of cities and countries. Environmental indicators are collected more frequently at the national and city levels. Moreover, objective measures of environmental performance are relatively scarce for historical analyses. To address these limitations, we construct our index based on metadata provided by OECD statistics, following a thorough investigation of public databases. This enables further comparative analysis across locations. At the city level, the OECD Cities Statistics database encompasses various dimensions, including economic, environmental, and territorial organization, through 112 indicators. It covers 41 countries, incorporating data on 1,389 cities and 1,271 functional urban areas (FUAs). The OECD has established a standardized definition of FUAs across the countries studied. A FUA is defined as a city along with its commuting zone, representing its economic and functional significance, as reflected in the daily commuting patterns of its inhabitants. Using FUAs instead of administrative city boundaries provides a more relevant framework for our environmental performance index. The administrative delimitation of a city arbitrarily constrains the analysis, as it does not align with economic reality from a territorial perspective. FUA values are primarily derived by downscaling indices from regional data, assuming the variable of interest follows the same distribution as population density. Additionally, FUA values are computed by aggregating local administrative data at the FUA level or by processing geolocated data using geographic techniques (OECD, 2022). First, we identified relevant variables from the OECD Cities Statistics at the FUA level, as they are less frequently collected than those at the national level. Once identified, we then searched for their counterparts at the country level to enable comparison. However, we could not account for all dimensions outlined in the conceptual framework. Among the 112 indices in the Cities Statistics database, 88 were calculated for FUAs. Only seven environmental dimensions are covered: air pollution, protected areas, public transport, green spaces, flood risk, fire risk, and heat stress. Unfortunately, data on protected areas, green spaces, and public transport access are only available for 2017, 2020, and 2022. Additionally, information on the share of the population exposed to flood risk is only available for 2015. As a result, we excluded it from the application, as its variation over time could not be analyzed. Therefore, the application measures a reduced version of the DEPI. Due to data limitations, only two of the six theoretical dimensions are considered: air quality and climate hazard management.

4.2 Outcome selection – FUA level

The variables selected at the FUA level include: the mean population exposure to PM2.5 air pollution, the proportion of built-up areas exposed to river flooding (with a 50-year return period), the proportion of built-up areas exposed to coastal flooding (50-year return period), the share of the population exposed to at least one forest fire, and the number of days experiencing strong heat stress (UTCI > 32 °C). The mean population exposure to PM2.5 is downscaled through geographic processing, using data derived from a geographic shapefile containing boundary information and from the OECD Environment Directorate[2]. The share of built-up areas exposed to river flooding represents an assessment of population exposure. Data was collected using River Flood Hazard Maps at both European and global scales. These maps rely on a regional dataset with a spatial resolution of 250 meters for OECD countries within Europe and the Mediterranean Basin, and a global dataset with a 1-kilometer spatial resolution for other OECD countries. These datasets identify areas susceptible to river flooding based on various return periods. This measure is subsequently disaggregated through geographic processing to derive FUA-level variables. The methodology used to construct the share of built-up areas exposed to coastal flooding is not explicitly documented in the Metropolitan Database documentation or the Climate and Environment Regional Statistics documentation. However, it is reasonable to assume that it follows a similar approach to the river flooding variable. The share of the population exposed to at least one forest fire is calculated by integrating monthly wildfire perimeters and applying a 5-kilometer buffer. This process uses data from the Joint Research Center (JRC) Global Wildfire dataset. Population exposure is then estimated using the Global Human Settlement Population layer. Finally, FUA-level values are computed through geographic processing. The number of days with strong heat stress (UTCI > 32 °C) represents the annual count of days experiencing strong heat stress. The OECD derives this measure using geolocated data from the Copernicus Climate Data Store. The process involves calculating the daily maximum temperature, applying a 32 °C threshold, and summing the results annually to produce gridded datasets of strong heat stress days. These datasets are then disaggregated through geographic processing to obtain FUA-level variables.

4.3 Outcome selection – National level

We integrate multiple databases to compile all necessary information at the national level. The selected variables include the mean population exposure to PM2.5 air pollution, the proportion of built-up areas exposed to river flooding (50-year return period), the proportion of built-up areas exposed to coastal flooding (50-year return period), the percentage of the population exposed to wildfires, and the percentage of the population exposed to extreme heat days (Table 1). The mean population exposure to PM2.5 was derived from the *Exposure to PM2.5 in Countries and Regions* database. This metric is computed using the *Global Burden of Disease 2017* project data, which integrates satellite observations, chemical transport models, and ground-based monitoring station measurements. Population exposure is then estimated using gridded population datasets from the JRC Global Human Settlement project. We use data from the OECD Climate and Environment Regional Database regarding the proportion of built-up areas exposed to river and coastal flooding. National values were computed by aggregating regional shares using an arithmetic mean. This methodology and dataset align with those used for variables measured at FUA level. However, specific details were not provided in the dataset regarding coastal flooding exposure. The share of the population exposed to wildfires was estimated using the Global Human Settlement Layer population grids, which quantify the population residing in areas classified as having very high or extreme fire danger according to the Fire Weather Index. This data was sourced from the *Green Growth Indices* database. Finally, the percentage of the population exposed to extreme heat days was also obtained from the *Green Growth Indices* database. In this context, "population exposure" refers to the proportion of the population experiencing at least one to a maximum of fourteen extreme heat days per year, where extreme heat days are

[2] While the exact computation method is not specified, we assume it follows the same approach as the country-level variable.

defined as those with a maximum daily temperature exceeding 35°C. Table 2 summarizes the selected variables at both local and national levels.

Table 1: Variables included in the applied composite index according to territorial level.

	Functional Urban Area	Country
Negative Impact	Mean population exposure to PM2.5 air pollution	Mean population exposure to PM2.5 air pollution
	Share of built-up area exposed to river flooding (50-year return period)	Aggregation of the TL2 level share of built-up area exposed to river flooding (50-year return period)
	Share of built-up area exposed to coastal flooding (50-year return period)	Aggregation of the TL2 level share of built-up area exposed to coastal flooding (50-year return period)
	Share of the population exposed to at least one forest fire	Percentage of population exposed to wildfire
	Days of strong heat stress (UTCI > 32°C)	Percentage of population exposure to hot days (maximum daily temperature exceeds 35° C)

Source: authors.

4.4 Country and Period Selection

The reduced version of the DEPI is computed annually from 2001 to 2020 for ten countries and their corresponding FUAs. This twenty-year period allows for an assessment of the evolution of environmental performance at national and FUA levels, providing insight into which territorial scale exhibits better environmental management over time. The OECD countries selected for the final database were chosen to represent diverse regional contexts, with two countries from each continent. Specifically, the database includes Australia and New Zealand for Oceania, the United States (US) and Canada for North America, Mexico and Colombia for South America, Japan and South Korea for Asia, and Belgium and Sweden for Europe. The following sub-section details the raw data processing and presents the final database used for index computation.

4.5 Final database processing and DEPI calculation

This section describes the construction of our final database and the computation of the DEPI results. We select the variables of interest (Section 4), focusing on those with a negative impact as well as the relevant periods, countries, and their respective FUAs from each of the previously mentioned datasets. These observations are then merged to create a unified database.

The merged database (including all FUA values) contains 37.25% zero entries, corresponding to 19,856 out of 53,300 rows. The most affected variables are primarily those related to shares. Specifically, the share of the population exposed to at least one fire accounts for 28.71% of zero observations (both at the FUA and country levels). Other affected variables include the days with strong heat stress at the FUA level (3.35%) and exposure to hot days at the country level (0.26%). Additionally, the share of built-up areas at flood risk represents 13,436 values or 67.66% of zero entries. Zeros are predominantly observed at the FUA level, accounting for 19,698 cases, or 99.20% of the total. Moreover, 771 pairs of geolocations and variables consistently recorded a value of ‘0’ across all years. Among these, 49 pairs contained only a single non-zero value throughout the period at the FUA level, making them unsuitable for analyzing trends over time. These two groups comprise 16,351 observations, meaning 82.34% of the recorded values are equal to zero. Furthermore, for FUAs and countries where a variable is conceptually irrelevant (such as coastal flooding in inland regions) these cases are coded as "NA." Using "NA" for missing values allows us to compute 100 baseline indices and then derive their geometric mean to calculate the DEPI for each year. This ensures that only meaningful and varying values contribute to the DEPI while excluding variables where the risk or occurrence is inherently null. The database used for DEPI computation is structured in a long format, where each row represents an observation corresponding to a specific location, year, and variable. The included variables are as follows:

- 'LOCATION' informs us about the 3-character country code of each location. It contains 10 unique country codes associated with selected countries.
- 'GEO' provides granular information about FUAs' OECD code and replicates the 3-character country code for country-level observations. This dataset includes 533 unique values and, thus, 523 different FUAs across 10 countries.
- 'TIME' accounts for the year the observation occurred. It ranges from 2001 to 2020.
- 'VAR' includes a variable code for each result under consideration, representing the seven variable codes included in our application. Three of them have the same codes for country and FUA level, and four differ but still convey similar information.
- 'VALUE' carries values associated with each triple GEO-TIME-VAR ranked from 0.008 to 366.

First, we add two columns to this database to calculate the DEPI. One contains the first no-missing value of matching GEO-VAR pairs as the initial value on which 100 indices are calculated. The second is the result of the base 100 computations. We then grouped the observations by geolocation and year to calculate the geometric mean for every variable per year and geolocation, obtaining the yearly DEPIs for every FUA and country. Finally, all FUA results by country are averaged to get a unique value for the FUA level per year. The DEPI values ranged from 34.52 (Japan at the country level in 2007) to 295.60 (New Zealand at the country level in 2017). The mean and median of DEPI values are approximately 102.15 and 100.00, respectively. In summary, half of the results indicate a net reduction in harmful environmental impacts, while the other half suggest an increase. The bottom quartile of the results exhibits a decrease of at least 12.05% from the baseline level. In contrast, only a quarter of the results show a deterioration exceeding 14.23% of their initial environmental performance, primarily compared to their 2001 baseline. Table 2 presents the descriptive statistics discussed above.

Table 2: Descriptive statistics for the global DEPI results

Minimum	1st Quarter	Median	Mean	3rd Quarter	Maximum
34.52	87.95	100.00	102.15	114.23	295.60

Source: authors.

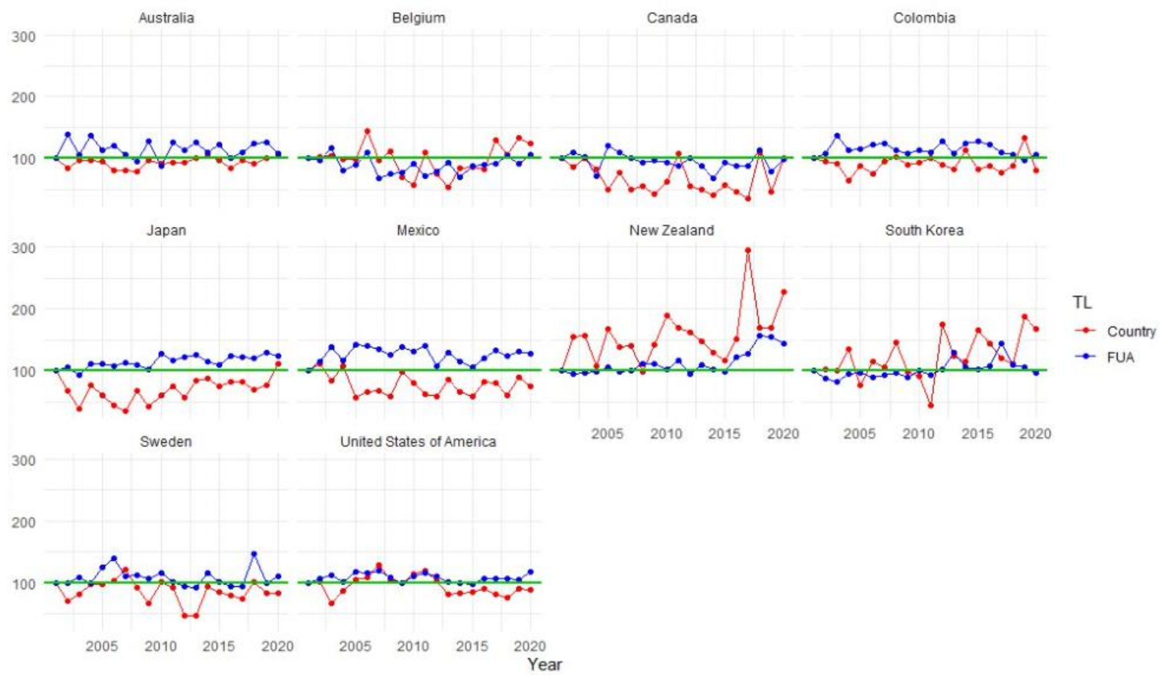
We analyze the overall results in the following section.

-5-
Results

The results are first presented at the national level, followed by an analysis at the territorial level. Various graphical representations then illustrate which level demonstrates better environmental management over time.

5.1 Country level

Environmental management appears to be more effective nationally than at the FUA level in Australia, Canada, Colombia, Japan, Mexico, and Sweden. However, results are more ambiguous for Belgium, South Korea, and the United States. In the U.S., national and FUA-level trends intersected several times before 2012, after which the national level consistently outperformed the FUA level. New Zealand is the only country where the national level underperforms the FUA level almost every year, with 2008 being the sole exception. At the national level, Canada, Japan, and Mexico exhibit the greatest reductions in harmful environmental outcomes within our sample. Among FUAs, Belgium demonstrates the best overall performance. Additionally, in Canada, South Korea, Sweden, and urban areas in the U.S., DEPI trends closely follow their baseline values. Similar patterns are observed in Australia and Colombia. Meanwhile, Japan and Mexico display an inverse relationship, with DEPI scores increasing at the FUA level while decreasing at the national level. These countries were selected to assess the environmental performance of nations across different continents within the OECD. Our findings indicate that variations in results are just as pronounced between countries on the same continent as they are between countries on various continents. We conducted paired t-tests for each continent at both levels to investigate this. All but one test confirmed that differences between countries within the same continent were not statistically significant[3]. Overall, no clear continental effect would systematically explain the observed DEPI results. Given the large number of FUAs considered for each country, their evolution appears smoother than national-level DEPI. Extreme values at the FUA level are mitigated by the geometric mean used in computation and by aggregation through an arithmetic mean. In the following paragraphs, we look at each country, analyzing how national results contribute to specific fluctuations. Additionally, the DEPI reveals a strong influence of country-specific risks, which could help identify vulnerable areas and potential opportunities for improvement.



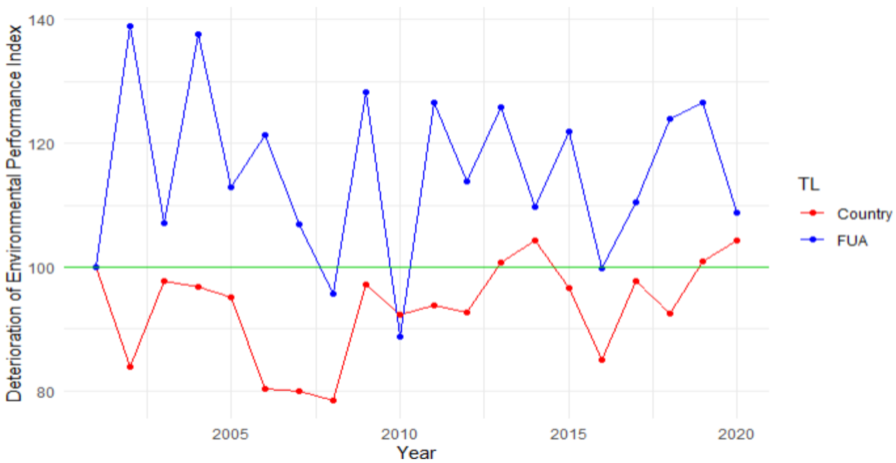
Graph 1: Evolution of DEPI for each country over the same period (2001–2020). *Note: The green horizontal line for y=100 represents normalization to base 100. On the one hand, when a country or FUA point is above this point, its environmental performance deteriorates compared with its reference level. On the other hand,*

[3] The only exception was found at the FUA level between Australia and New Zealand.

when they are below, their performance improves. This means that they are reducing their harmful effects on the environment compared with their reference level. We need to subtract 100 from the result to read the percentage variation.

5.1.1 Australia

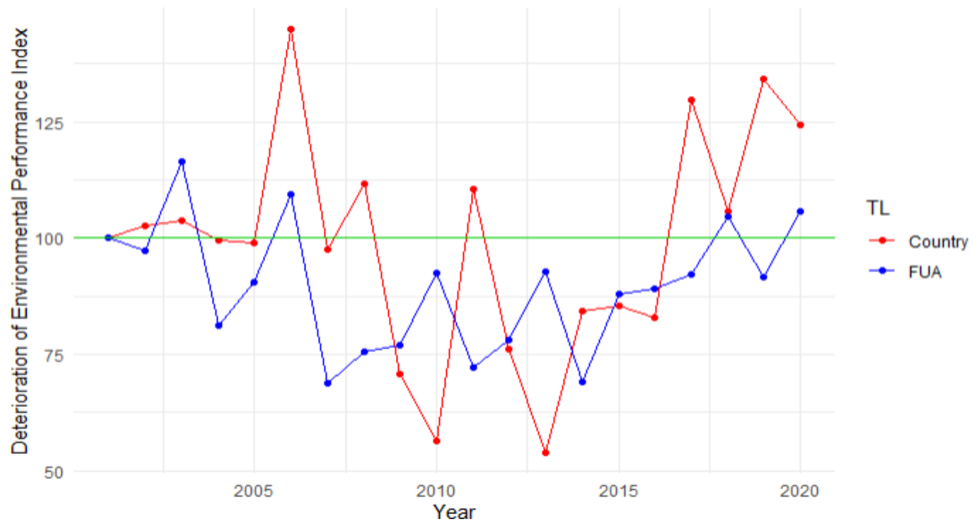
The evolution of the DEPI index in Australia is quite variable at both levels. At the national level, the minimum was 78.47 in 2008, representing an average decrease of 21.53% in environmentally damaging results compared to the 2001 level. The maximum is 104.25 in 2020, representing an average increase of 4.25%. At the FUA level, the DEPI value reached its minimum in 2010, 88.72 (-11.28% in 2001), and its maximum in 2002, 138.91 (+38.91% in 2001). The national coastal flood risk was approximately 50% below its baseline (0.12% in 2001) in 2006 and 2007. This influenced the overall index, as most other base-100 values remained close to 100. The country's 2008 result can be attributed to a halving of fluvial flooding risk and a 30% reduction in the population exposed to wildfire risk. In 2010, the FUA level was the only instance where it exceeded the national level, with a difference of 3.51%. Australia's local DEPI appears to be primarily driven by the proportion of the population exposed to at least one wildfire, which has shown the greatest variation over time. A paired t-test comparing index results at both levels confirms that national and FUA levels exhibit significantly different average measures of environmental degradation over time. Based on these findings, we conclude that environmental management is more effective at the national level than at the city level in Australia. However, both levels have shown an overall increase in environmental degradation since 2019, suggesting a recent reversal of the country's past performance.



Graph 2: Australia's DEPI by territorial level over 2001–2020.

5.1.2 Belgium

The DEPI values exhibit a relatively wide range at the national level, with a minimum of 53.92 in 2013 and a maximum of 144.88 in 2006. On average, negative environmental changes varied between -46.08% and +44.88% compared to their initial values. At the FUA level, the range is narrower, with a local minimum of 68.76 (a decrease of 31.24%) and a maximum of 116.51 (an increase of 16.51%). In Belgium, DEPI fluctuations are largely driven by the proportion of the population exposed to hot days. This data is available for only 10 of the 20 years considered in the analysis, yet it produces extreme results when reported. For instance, in 2003, the reference value was 27.8%, which surged to 79.4% in 2006, explaining the sharp increase in the DEPI that year. No data is available until 2009, when the value drops to 5.3%, resulting in a base-100 index of 19.06. A similar trend was observed in 2010, decreasing to 2.1%. The next recorded value in 2015 shows a 51% decrease compared to the reference year. However, in the last three years of the period, values consistently exceeded the reference level, with base-100 indices of 180.57, 336.33, and 329.13, respectively. Coastal flooding risk also contributes to index variability, albeit to a lesser extent. When measured, its values increase by approximately 50% compared to the reference year, except when data is missing ("NA"). This occurs in 7 out of the 10 years in which coastal flooding is considered. The sharp increase in 2017 is particularly notable, as the share of built-up areas at risk of coastal flooding surged by 207.54% compared to its 2002 reference value, rising from 4.74% to 14.58%. Given these fluctuations, it is difficult to draw definitive conclusions about which territorial level—national or FUA—is better managed from an environmental perspective over time in Belgium. A paired t-test comparing DEPI results at both levels indicates that, on average, national and FUA levels exhibit statistically similar patterns of environmental degradation. However, visually, FUA-level results have been consistently better than national-level results since 2017.

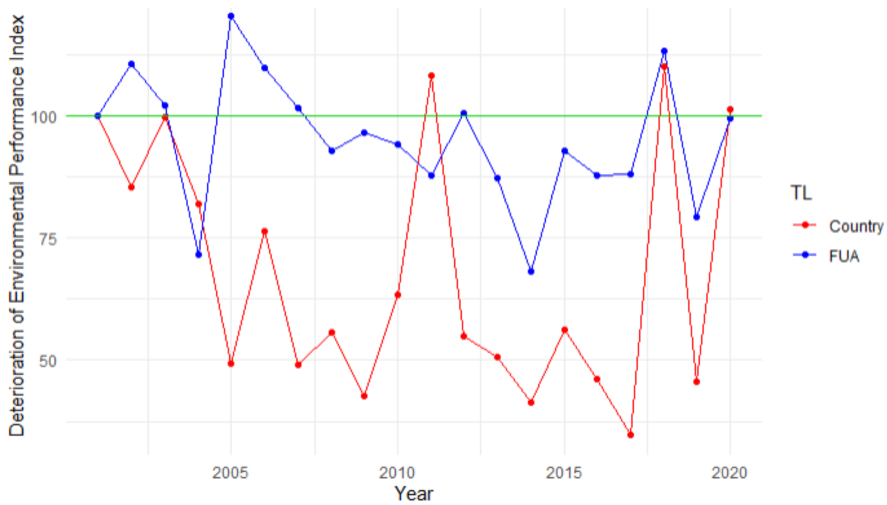


Graph 3: Belgium DEPI by territorial level (2001-2020).

5.1.3 Canada

We observe a greater range of results at the country level than at the FUA level in Canada. Nonetheless, a paired t-test comparing index results confirms that national and FUA levels present significantly different average measures of environmental degradation over time. Local values range from 68.10 in 2014 to 120.40 in 2005, while national values vary between 34.77 in 2017 and 110.06 in 2018. Canada's country-level DEPI results are primarily influenced by the share of the population exposed to hot days and coastal flood risks. In 2001, 20% of the population was exposed to hot days. The normalized base-100 index remained below 25% for twelve subsequent years. And it was even under 5% for some of those years. The sharp increase in 2011 highlights this variability, with the base-100 index rising dramatically from 6 in 2010 to 144.5 in 2011, before dropping back to 35.5 in 2012. Coastal flood risk remained consistent with its 2001 baseline value of 4.85%, except for 2006, 2007, 2009, 2012, and 2017, when it dropped below 0.67%. These declines contributed to the overall reduction observed during those years. In contrast, increases observed in 2011 and 2018 were partly driven by the share of the population exposed to wildfires. This share rose by approximately 70% in 2011, climbing from its initial value of 0.68% in 2001 to 1.21% in 2011. A similar pattern was observed in 2018 when wildfire exposure reached 1.16%. Over the entire period, national values outperformed local ones. However, by 2020, both had returned to their baseline levels, suggesting that the improvements observed in earlier years were effectively offset. This indicates that the overall results have not significantly changed since

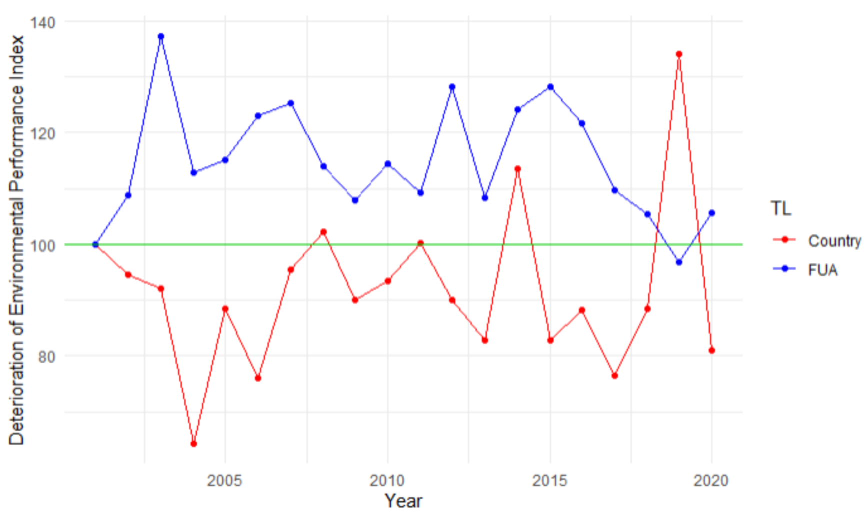
2001, despite periods of progress.



Graph 4: Canada DEPI by territorial level.

5.1.4 Colombia

Colombia's DEPI values are relatively stable, with minor annual variations. A paired t-test comparing DEPI results confirms that the national and FUA levels exhibit significantly different average measures of environmental degradation over time. The lowest value was recorded in 2004, at 64.33, reflecting a 35.67% reduction in environmentally harmful outcomes. Conversely, the highest value was 134.12 in 2019, representing a 34.12% increase. At the city level, DEPI values range from 96.81 in 2019 to 137.18 in 2003. Note that 2019 is the only year in which local level improved. In 2004, river flood risk was significantly reduced by 72.17% compared to its 2001 level, dropping from 14.97% to 4.16%. However, 2019 is the only year when the national DEPI exceeded the FUA level. That year, flood risk soared to 174.86% of its 2001 baseline for coastal areas and 134.46% for riverine areas compared to baseline values of 0.008% and 14.97%, respectively. Flood risk was also notably high in 2014 and 2019, with DEPI results exceeding the base-100 threshold at 113.50 and 134.12, respectively. As a result, Colombia's national-level performance consistently outperformed the urban level except for one year.

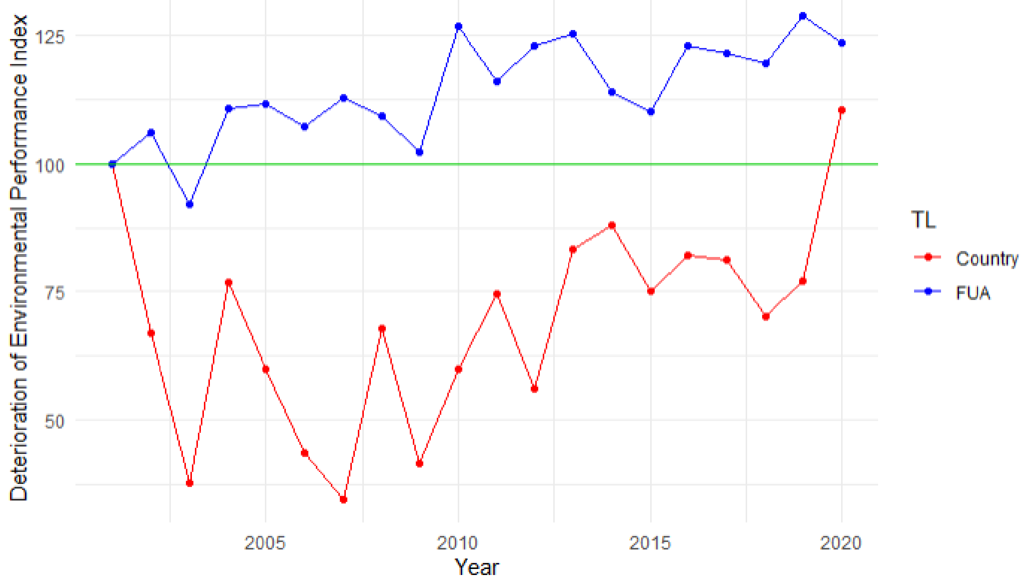


Graph 5: Colombia DEPI by territorial level (2001-2020).

5.1.5 Japan

Japan's local-level DEPI index fluctuates but follows a general upward trend, increasing from 92.02 in

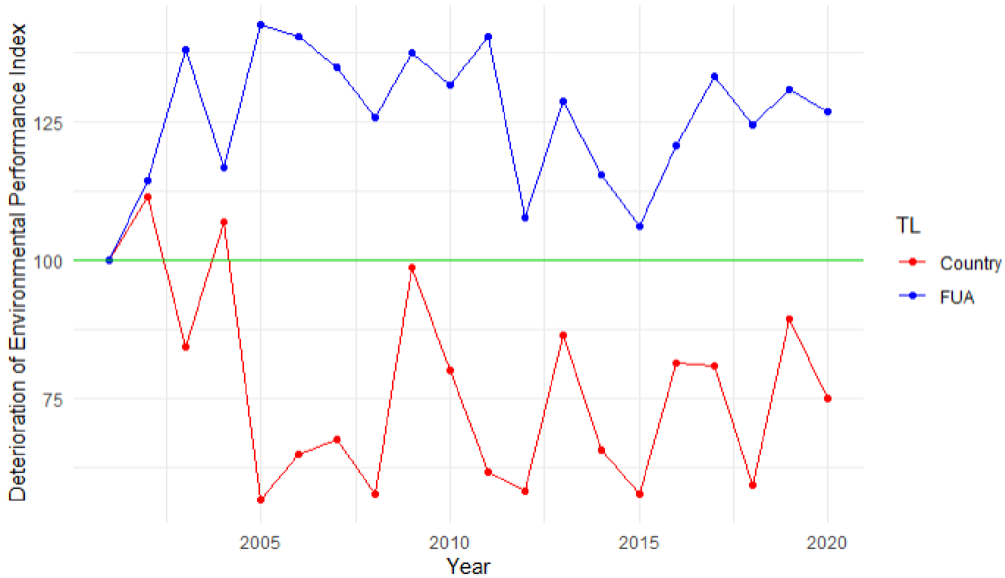
2003 to 128.83 in 2019. It consistently remains above the baseline, indicating a steady decline in environmental performance. In contrast, the national-level index shows greater variability, rising from 34.52 in 2007 to 110.50 in 2020, the only year since 2001 to record a deterioration relative to the baseline. A paired t-test comparing index results confirms a significant difference in average environmental degradation between the national and FUA levels over time. Flood risk is the primary driver of these results in Japan. Other indices exhibit low year-to-year variations, except for the share of the population exposed to hot days in 2009, which was unusually minimal at 3.9%, compared to an average of 41.28%. By 2020, the DEPI index surpassed 100, driven by increased urban exposure. Urbanized areas saw a 34.99% rise in exposure, while the share of the population affected by hot days increased by 9 percentage points, pushing the hot-day exposure index to 117.01 on a base-100 scale. Meanwhile, PM2.5 concentrations rose by only 0.3% compared to 2001. However, a 5.88% reduction in built-up areas at risk of river flooding was insufficient to offset increases in other factors. Throughout the review period, environmental management outcomes at the national level consistently outperformed those in FUAs.



Graph 6: Japan DEPI by territorial level (2001-2020).

5.1.6 Mexico

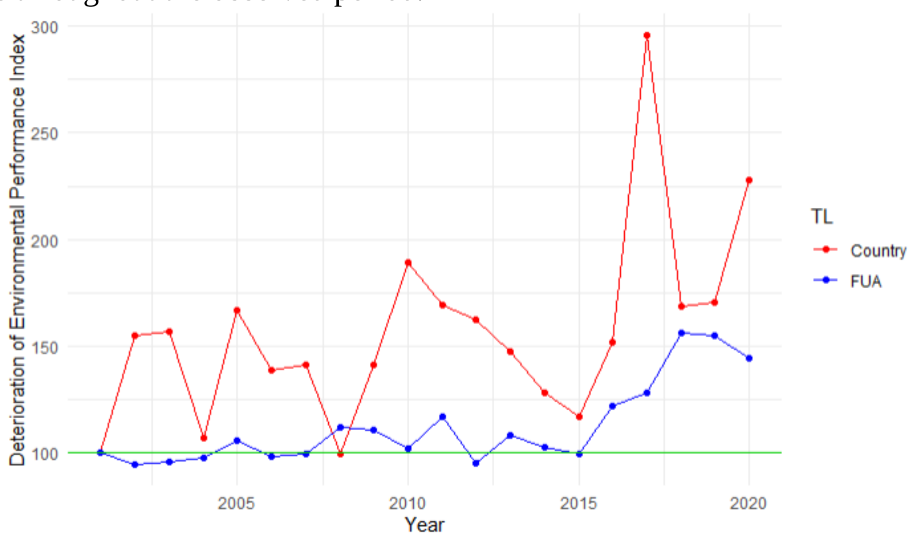
Mexico's national DEPI shows a clear decline in adverse environmental outcomes since 2004. Values range from 111.44 in 2002 to a minimum of 56.78 in 2005, with only two instances exceeding the 2001 reference level. In contrast, local DEPI results remain consistently above their 2001 baseline, rising from 100 in 2001 to 126.97 in 2020, with a peak of 142.61 in 2005. As in other cases, Mexico's overall environmental performance is heavily influenced by fluctuations in flood risks, while other factors play a less significant role. The share of built-up areas exposed to coastal flooding, measured in base-100 values, fluctuates from a minimum of 29.97 in 2017 (0.037%) to a maximum of 270.30 in 2005 (0.337%), compared to the 2001 baseline of 0.125%. River flood risk, however, remains relatively low, consistently below 1%. The base-100 index for river flood risk reached a minimum of 2.13 in 2005 and a maximum of 126.28 in 2017. The proportion of areas exposed to river flooding was 31.85% in 2001 and surpassed this level only in 2017, reaching 40.22%. Additionally, the proportion of built-up areas at risk remained generally below 10%, with a minimum of 0.68% in 2005, contributing to the decline in the index that year. A paired t-test comparing national and local DEPI results confirms a significant difference in average environmental degradation over time. This suggests that Mexico consistently achieves better environmental management at the national level than at the city level. Among all the countries analyzed, Mexico exhibits the most consistent reduction in negative environmental outcomes.



Graph 7: Mexico DEPI by territorial level (2001-2020).

5.1.7 New Zealand

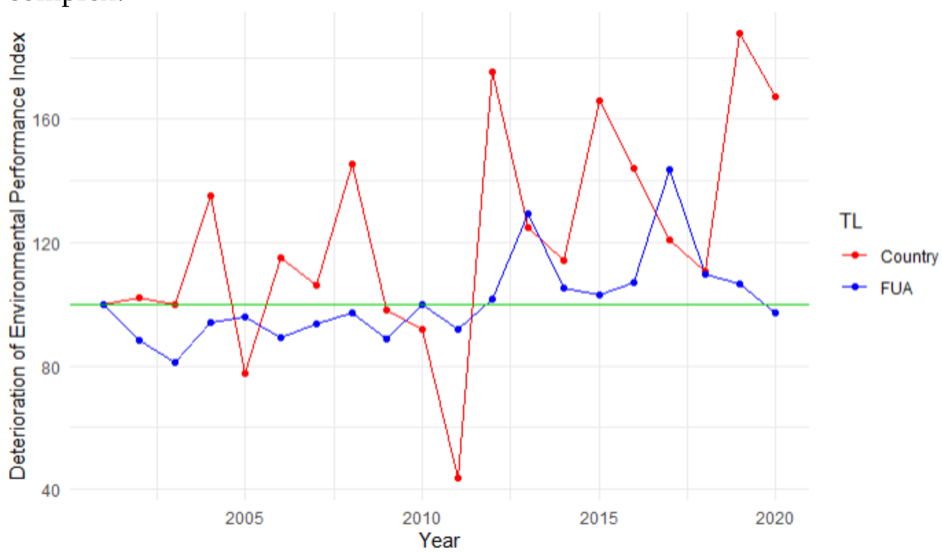
For its FUAs, New Zealand exhibits a steady upward trend in DEPI values. The lowest recorded value was 94.63 in 2002, while the peak occurred in 2018 at 156.49. This upward trend has accelerated since 2015. In contrast, national-level DEPI results are more variable, ranging from 99.26 in 2008 to a maximum of 295.60 in 2017. Notably, 2008 is the only year when the national DEPI dropped below the base-100 reference level. A paired t-test comparing DEPI results confirms a significant difference in average environmental degradation levels between national and local scales over time. New Zealand's national DEPI is heavily influenced by the proportion of built-up areas exposed to coastal flood risk. This share started at a relatively low baseline of 0.091% in 2001 and increased significantly over time, though it remained below 1%. The highest recorded values were 0.287% in 2005 and 0.266% in 2018 and 2019. The sharp rise in national DEPI in 2017 can be attributed to an increase in the population exposed to wildfire risk, which surged from 0.04% in 2009 (the earliest available data point) to 1.06% in 2017, resulting in a base-100 index of 265 for that year. At the urban level, DEPI results consistently outperform national-level outcomes, except for 2008 when the national DEPI was 12.61 percentage points lower. Among the countries in the sample, New Zealand is unique in demonstrating better environmental management at the city level than at the national level. However, local and national DEPI results remain above their reference levels throughout the observed period.



Graph 8: New Zealand DEPI by territorial level (2001-2020).

5.1.8 South Korea

The DEPI at the FUA level exhibits greater consistency than the national level. National DEPI values fluctuate widely, ranging from a minimum of 43.72 in 2011 to a maximum of 187.70 in 2019. Conversely, local DEPI values show less variation, with a minimum of 81.17 in 2003 and a maximum of 143.73 in 2017. Note that urban areas performed well until 2012, maintaining negative results below the 2001 baseline. At the national level, South Korea's trajectory is largely driven by the share of the population exposed to hot days, which accounts for much of the observed variability. The baseline in 2001 was 10.6%, but this share fluctuated dramatically, reaching a minimum of 0.03% in 2011 and peaking at 76.7% in 2018. As a result, the base-100 index varied significantly, from a minimum of 2.83 to a maximum of 723.58. Other variables exhibited similarly smaller fluctuations over the years, further amplifying the influence of hot-day exposure on national DEPI outcomes. Although a paired t-test confirms a significant difference between average DEPI values at the national and city levels, drawing clear conclusions about South Korea's territorial environmental management remains challenging. This ambiguity stems primarily from the interconnectedness of national and local indices, making direct comparisons complex.

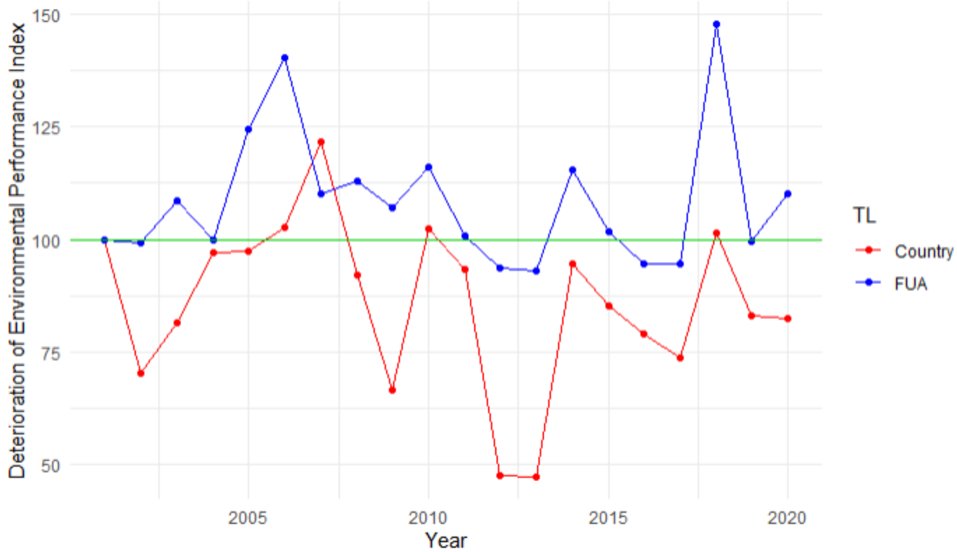


Graph 9: South Korea DEPI by territorial level (2001-2020).

5.1.9 Sweden

At the national level, only four DEPI values exceed the 2001 reference. National DEPI scores range from a minimum of 47.22 in 2013 to a maximum of 121.57 in 2007. Conversely, at the city level, only four results fall below the 2001 reference, with local DEPI values ranging from a minimum of 92.96 in 2013 to a maximum of 147.79 in 2018. The rapid decline in national DEPI during certain years is primarily driven by the variability in the share of built-up areas exposed to coastal and river flooding risks. For coastal flooding, the share reached its lowest point in 2013 at 0.379%, compared to the 2001 baseline of 2.353%. This corresponds to a base-100 index of 16.11 in 2013. The values only exceeded the baseline in 2006 and 2007, at 2.612% and 3.113%, respectively. River flooding risk shows similarly high variability, starting with a baseline value of 8.625% in 2001. This share decreased to 5.875% in 2012, rose by 1.1 percentage points in 2013, and peaked at 12.077% in 2014. Consequently, the base-100 index for river flooding risk increased sharply from 80.99 in 2013 to 140.01 in 2014, accounting for the steepest drop in the DEPI graph. A paired t-test comparing DEPI results confirms that national and city levels exhibit significantly different average measures of environmental degradation over time. The national level consistently outperforms the city level nearly every year, except for 2007. That year, the local FUA

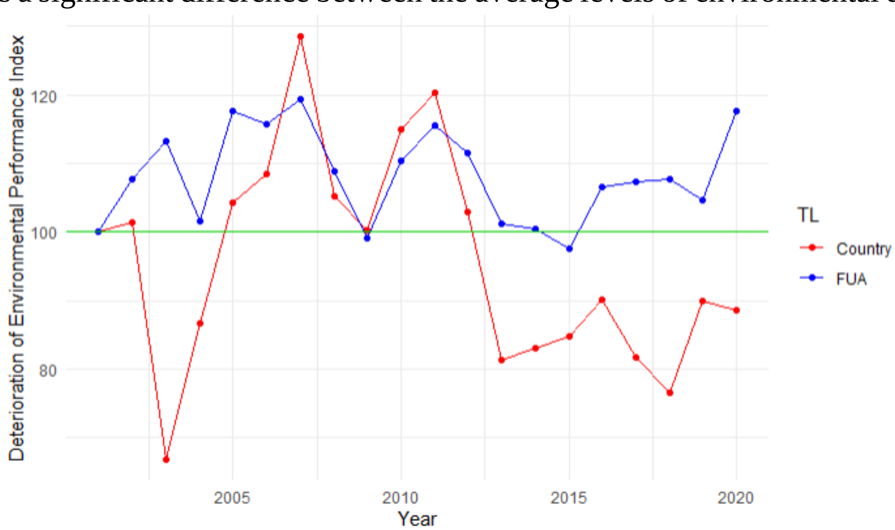
DEPI stood at 110.14, while the national DEPI was slightly higher at 121.57. Both coastal and river flood risks at the national level had risen to over 30% of their initial levels, contributing to the divergence in results.



Graph 10: Sweden DEPI by territorial level (2001-2020).

5.1.10 United States of America

The USA's DEPI values range from 66.83 in 2003 to 128.47 in 2007. DEPI values are consistently higher, fluctuating between a minimum of 97.50 in 2015 and a maximum of 119.37 in 2007 at the city level. Notably, local DEPI exhibits less variability compared to the national index. The first decline in the national DEPI in 2003 can be attributed to a combination of below-benchmark values for flood risk and exposure to hot days, alongside improvements in forest fire management. A similar pattern emerged in 2013. In contrast, 2007 saw a sharp increase in DEPI due to significantly higher-than-baseline levels of river flood risk and population exposure to forest fires, which resulted in base-100 indices of 162.23 and 223.47, respectively. Additionally, coastal flood risk surged in 2010 and 2011, contributing to the second peak illustrated in Graph 11. By 2012, the national-level DEPI indicated better environmental management than at the city level. However, before that year, results varied depending on the specific year examined. Despite this variability, a paired t-test comparing national and local DEPI values confirms a significant difference between the average levels of environmental degradation over time.

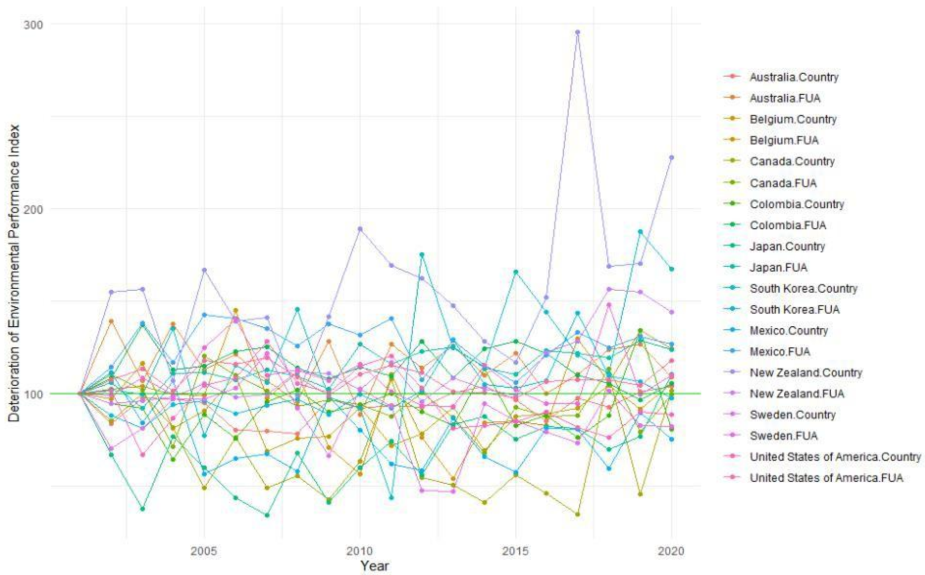


Graph 11: USA DEPI by territorial level (2001-2020).

The next subsections analyze the joint evolution of each level.

5.2 Evolution of DEPIs at different territorial levels

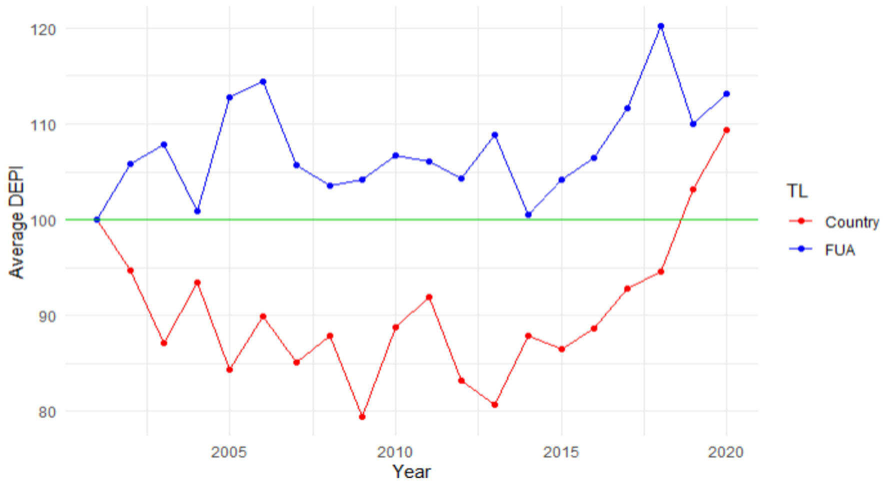
In the context of the 2015 Paris Agreement, it is important to assess whether the implementation of international commitments to mitigate the environmental impact of human activities is reflected in actual outcomes. However, we observe no significant change after 2015. The results appear to follow their pre-existing trajectory, unaffected by the announced commitments. Graph 12 presents DEPIs for each territorial level on a single chart, illustrating twenty different results.



Graph 12: DEPI by territorial level (2001–2020).

5.3 Local vs. national

Finally, we use a geometric mean to calculate the DEPIs for all countries and FUAs. On average, environmental management is consistently better at the national level than at the city level each year. Moreover, the Paris Agreement does not appear to have been effective, as both values have increased since 2015. Ideally, environmental policies should be implemented at all levels to effectively mitigate the impacts of climate change. However, local-level policies would greatly benefit from improved implementation, as their performance has deteriorated over time.



Graph 13: Overall average DEPI by territorial level (2001–2020).

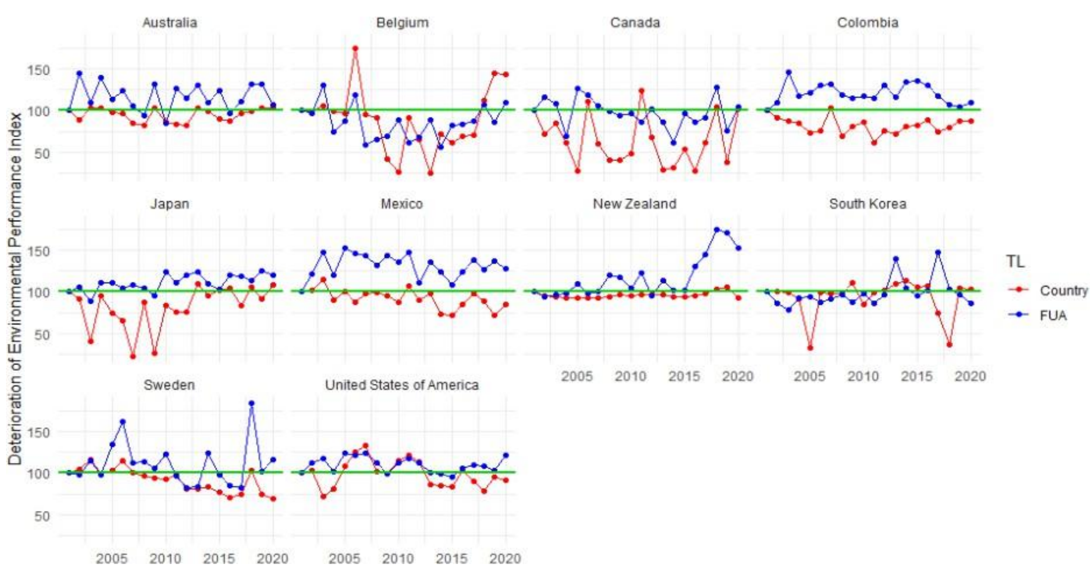
In the next section, we discuss the robustness of the index.

-6-
Robustness analysis

Robustness is assessed through two approaches. First, we compare the original results with an alternative version of the applied index. Second, we evaluate the theoretical framework and the application of DEPI.

6.1 Alternative version of the DEPI

We recognize that modifying input variables or applying different weights could alter the overall results. Therefore, we calculated an alternative DEPI, excluding coastal and river flooding risks, as they were the primary sources of extreme values. Overall, the results and trends remain consistent with the original findings. Environmental performance tends to be stronger at the national level throughout the observed period, although some variations are year-dependent. Australia, Canada, Colombia, Japan, Mexico, and Sweden continue to perform better at national and city levels, indicating greater environmental deterioration in urban areas. In contrast, the territorial level with the best-managed environment fluctuates over time in Belgium and the United States. New Zealand and South Korea were excluded from direct comparisons with other countries. In the alternative DEPI, New Zealand exhibits a relatively stable trend at the national level, as only one variable was considered (the mean population exposed to PM2.5). South Korea's results remain ambiguous, generally staying close to the baseline except for two outliers at each level. To sum up, this alternative version reinforces confidence in our initial results. National-level performance in air quality and climate hazard management consistently surpasses that of urban areas.



Graph 14: Alternative DEPIs by territorial level (2001-2020).

6.2 Theoretical and practical evaluation

The integrity of composite indices primarily depends on the rigorous scrutiny of their theoretical framework, underscoring the need for full transparency. Robustness is achieved when every decision can be explicitly traced back to the index's intended purpose (Greco *et al.*, 2019; OECD, 2008). Accordingly, we present a multicriteria evaluation of the Depreciation of Environmental Performance Index. The evaluation method, outlined in Table 3, is based on the framework developed by Gadrey and Jany-Catrice (2016), which assesses an index's efficiency and methodological soundness as a measurement tool. There is no universally "correct" answer for each criterion; the overall evaluation depends on the intended goal and application of the indices. One notable area for improvement is the lack of public involvement in the development and use of the index, which significantly affects their perceived legitimacy. Additionally, the degree of consideration given to irreversible environmental effects could be enhanced. However, using a geometric mean introduces an inherent trade-off between outcomes, which may not fully capture these effects. Similarly, while one could argue that aggregation should be weighted—since not all environmental outcomes hold equal importance in management decisions—both weighted and unweighted approaches can be valid if well justified. On the positive side, both indices have a clearly defined objective: evaluating the environmental performance of government entities at various levels. The selection of outcomes was guided by relevant literature and remains flexible for further expansion. Moreover, the transparency of methodology and data processing is a key strength. The ability to compare results annually and track overall trends adds further value. Additionally, the indices allow for disaggregation by dimension, individual outcomes, and territorial levels, making them adaptable for specific assessments. DEPI incorporates only two dimensions, represented by five outcomes: four related to climate hazard management and one addressing air quality management. The applied version is less comprehensive regarding complementarity and coverage of environmental outcomes that reflect territorial ecological performance. However, it maintains strong data integrity and international comparability due to its reliance on the OECD database.

Table 3: Evaluation of technical and political aspects of DEPI

	Deterioration of Environmental Performance Index
A. Construction mode	
Nature of the initiative	Research article
Accounting consistency	Non-monetary valuation, comparing each outcome with its initial value
Data integrity	Reliable statistics, OECD datasets
Possible expansion	Yes, open to new data and new dimensions enlargement
Theoretical and conventional framework	Environmental performance outcomes chosen via dedicated literature
B. Dimensions and components	
Complementariness	Data restriction but main quantitative environmental outcomes included (air pollution, climate hazard via heat, flood and fire risks).
Objective or subjective measure	Objective measure
Number of dimensions	2 dimensions through five outcomes, relative simplicity
Choice and transparency of weighting	Unweighted geometric mean of base 100, complete transparency
C. Technical potential of the index for various use	
Temporal continuity, regularity of the data used	Normalization through the first non-zero value of each outcome on the chosen period. Rather strong regularity of OECD data
International comparability of variables and data sources	Strong comparability, single data source (OECD datasets)

Synchronicity and diachronicity	Comparison can be made for a single year from a starting point, as well as for its evolution over time.
Adjustability and disintegration	Strong, can be computed for any territorial level and declined for any outcome
Degree of consideration given to irreversible effects	Relatively weak via geometric means
D. Political perspectives	
Clear economic and/or social policy objective	Yes, evaluation of territorial environmental performances
Public decision-making tool	No, research project without public involvement
Possible use	An indicator of the sustainability of our development strategies, with quantified measurements of environmental performance to fuel discussion
Acquired legitimacy (media coverage, influence in public debate, lifespan of the index)	No coverage, short lifespan

Source: Gadrey &Jany-Catrice (2016), completed by the authors.

-7-

Conclusion

This article presents an innovative framework for calculating a new quantitative composite index. Its purpose is to evaluate environmental management across different territorial levels over time. Using OECD databases, we calculate a Deterioration of Environmental Performance Index for ten countries at two territorial levels. We find that national level is on average better environmentally managed than the city level. New Zealand is the only country in our sample that presents poorer results nationally in comparison with their urban areas. Further research is needed to unravel the mechanisms that explain these results. Global agreements are insufficient, as they are not reflected in the evolution of quantitative outcomes. Environmental policies still need to be applied at all levels for better effectiveness in mitigating climate change impacts. However, there is a particular need to improve the implementation of local-level policies. Despite establishing ambitious climate plans and mitigation targets, FUAs' performance has deteriorated over time at a greater rate than the environmental performance of their respective countries.

Data constraints occur because FUAs have recently collected data on some environmental outcomes, such as public transport access or green areas. Therefore, we did not calculate the entire concept proposed for our applied analysis. Nonetheless, in the OECD database, more environmental outcomes are accounted for at the city level since 2021. Moreover, data issues should be overcome soon as the subject gains relevance in public debates. Another solution would be to merge several databases to account for the larger variety of environmental outcomes. This would improve the overall understanding of how local and national environmental performance has evolved. However, this may influence the results if local and national variables are not collected and processed using the same methodology. We assume a sufficient degree of independence between the local and national levels of the same country to compare the index results. However, a complementary study on each state's territorial organization would help further explain observed differences. In addition, it could be interesting to analyze whether the results are mechanically driven by cities' natural exposure to climate hazard risk and migration movement through population-weighted measures. For instance, coastal and river flood risks usually present greater tension at the city level than at the national level, as important cities are often located near water access areas. At the same time, rural and mountain areas are usually less populated. Thus, the DEPI results show that urban areas are more sensitive to climate change threats than countries with better climate change mitigation policies.

Regarding the variability of results, we considered establishing threshold categories of variation to limit the influence of extreme base-100 values on the overall index. This issue arises particularly when initial values are very small, making subsequent increases appear disproportionately large. For example, if an initial share is 0.05% and then increases to 0.1%, the base-100 index doubles to 200. In contrast, a 0.05 percentage point increase for higher initial values has a much smaller impact on the base-100 index. To address this, we could define category-specific limits for base-100 results, ensuring that identical percentage increases of similar proportions are more appropriately accounted for. Further research is needed to identify relevant category thresholds. Additionally, the first-level outcome may influence how its evolution is measured over time. A given territorial level might reach a minimum threshold on an outcome, preventing further reductions. In such cases, the current DEPI would reflect this as neutral, maintaining values close to the baseline. Introducing additional differentiation thresholds at various levels for each outcome could provide a more comprehensive assessment of territorial environmental performance. An alternative approach for handling zero values could also be explored by implementing thresholds. This could involve discretizing changes into a binary variable distinguishing between increases and decreases from the baseline or categorizing variable evolution into meaningful thresholds. This methodology could be further developed in future studies.

Finally, a key limitation of this concept is the absence of involvement from public actors. As highlighted in Gadrey and Jany-Catrice's framework, the legitimacy and longevity of indices are significantly diminished without public participation. To address this, we consider collecting public input on the relative importance of each variable within categories through an anonymous survey would be relevant. Participants would rank each outcome based on its perceived relevance to environmental management within a jurisdiction. Future research could then explore the possibility of computing relative weights based on these responses.

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Appendix

1. Data processing

1.1 Useful for all processing

```
pacman::p_load(here, dplyr, tidyverse, readr, stringr, readxl, tidyr, psych, ggplot2, forcats)
here::i_am("_R_PROG.Rproj")

countries <- c("AUS", "CAN", "USA", "COL", "MEX", "BEL", "SWE", "KOR", "JPN", "NZL")
TL2_keep <- c("^AU", "^CA", "^US", "^CO", "^ME", "^BE", "^SE", "^KR", "^JP", "^NZ")
TL2_keep <- paste(TL2_keep, collapse = "|")
```

```
country_code <- c("AU" = "AUS",
                  "CA" = "CAN",
                  "US" = "USA",
                  "CO" = "COL",
                  "ME" = "MEX",
                  "BE" = "BEL",
                  "SE" = "SWE",
                  "KR" = "KOR",
                  "JP" = "JPN",
                  "NZ" = "NZL")

country_name <- c("AUS" = "Australia",
                  "CAN" = "Canada",
                  "USA" = "United States of America",
                  "COL" = "Colombia",
                  "MEX" = "Mexico",
                  "BEL" = "Belgium",
                  "SWE" = "Sweden",
                  "KOR" = "South Korea",
                  "JPN" = "Japan",
                  "NZL" = "New Zealand")

period <- 2001:2020
```

1.2 Functional Urban Areas database

```
FUA_data_raw <- read.csv("FUA_CITY-en.csv")

FUA_data <- FUA_data_raw %>% filter((TL == "FUA"))
FUA_data <- FUA_data %>% filter((LOCATION %in% countries))
FUA_data <- FUA_data %>% filter((TIME %in% period))

FUA_data <- FUA_data %>% select(LOCATION, GEO, TIME, VAR, Value)

var_keep <- c("PWM_EX",
              "FLOOD_R_RP50_BUILT_SH",
              "FLOOD_C_RP50_BUILT_SH",
              "FIRES_POP_SH",
              "HEAT_STRESS_DAYS_UTCI32")
FUA_data <- FUA_data %>% filter((VAR %in% var_keep))

summary(FUA_data)
```

```
##    LOCATION              GEO                 TIME           VAR
##  Length:52300       Length:52300       Min.   :2001   Length:52300
##  Class :character   Class :character   1st Qu.:2006   Class :character
##  Mode  :character   Mode  :character   Median :2010   Mode  :character
##                                        Mean   :2010
##                                        3rd Qu.:2015
##                                        Max.   :2020
##      Value
```

```
## Min.    :  0.00 ##
1st Qu.:   0.00
## Median : 3.70 ##
Mean    :  23.15  ##
3rd Qu.: 17.00  ##
Max.    :366.00
```

```
print(unique(FUA_data$VAR))
```

```
## [1] "PWM_EX"                    "HEAT_STRESS_DAYS_UTCI32"
## [3] "FLOOD_R_RP50_BUILT_SH"  "FIRES_POP_SH"
## [5] "FLOOD_C_RP50_BUILT_SH"
```

```
#Cleaning the environment
rm(list=c("FUA_data_raw", "var_keep"))
```

1.3 Countries database

```
#Flood risk information
country_flood <- read.csv("REGION_level_ENV.csv")
country_flood <- country_flood %>% select(-c(Territorial.Level,Year, Flag.Codes, Flags))

  #keeping only the large region and country-level data
country_flood <- country_flood %>% filter(!(TL == 3))

flood <- c("FLOOD_R_RP50_BUILT_SH",
           "FLOOD_C_RP50_BUILT_SH")
country_flood <- country_flood %>% filter((IND %in% flood))

# length(unique(country_flood$TL))
#   #We have this information only at the large region (TL2) level

country_flood <- country_flood %>% filter(str_detect(REG_ID, TL2_keep))

country_flood <- country_flood %>% mutate(LOCATION = substr(REG_ID, 1, 2))

country_flood <-
  country_flood %>% mutate(LOCATION = recode(LOCATION, !!!country_code))

sum_country_flood <- lapply(flood, function(cat) {
  country_flood %>%
    filter(IND == cat) %>%
    group_by(LOCATION, TIME) %>%
    summarise(!!cat := mean(Value, na.rm = TRUE), .groups = "keep")
})

sum_country_flood <-
  Reduce(function(...)
    merge(..., by = c("LOCATION", "TIME"), all = TRUE), sum_country_flood)

country_flood_vf <- sum_country_flood %>%
```

```r
  pivot_longer(cols  =  c("FLOOD_R_RP50_BUILT_SH",
                          "FLOOD_C_RP50_BUILT_SH"),
                        names_to = "VAR",
                        values_to = "Value")

#Air pollution information
country_airpoll <- read.csv("EXP_PM2_5_COUNTRY.csv")
country_airpoll <- country_airpoll %>% select(c(COU, Year, VAR, Value))
country_airpoll <- country_airpoll %>% rename(c(LOCATION = COU, TIME = Year))
country_airpoll <- country_airpoll %>% filter((LOCATION %in% countries))

#Proxy heat stress and population exposure to fire information
country_hotdays_fire <- read.csv("GREEN_GROWTH_COUNTRY.csv")
country_hotdays_fire <- country_hotdays_fire %>% select(c(COU, Year, VAR, Value))
country_hotdays_fire <- country_hotdays_fire %>% rename(c(LOCATION = COU, TIME = Year))
country_hotdays_fire <- country_hotdays_fire %>% filter((LOCATION %in% countries))

country_hotdays_fire <-
  country_hotdays_fire %>% filter((VAR %in% c("HD_POP_IND", "FT_POP_IND")))

#Concatenating the final country database
country_data <-bind_rows(country_flood_vf,
                          country_airpoll,
                          country_hotdays_fire)

country_data <- country_data %>% mutate(GEO = LOCATION)
country_data <- country_data %>% select(LOCATION, GEO, TIME, VAR, Value)

country_data <- country_data %>% filter(TIME %in% period)

summary(country_data)
```

```
##     LOCATION             GEO                 TIME          VAR
##  Length:1000        Length:1000        Min.   :2001   Length:1000
##  Class :character   Class :character   1st Qu.:2006   Class :character
##  Mode  :character   Mode  :character   Median :2010   Mode  :character
##                                        Mean   :2010
##                                        3rd Qu.:2015
##                                        Max.   :2020
##
##      Value
## Min.  : 0.0000 ##
1st Qu.: 0.3648
##  Median :  6.2274
## Mean   :10.8028  ##
3rd  Qu.:13.7607   ##
Max.    :93.5000
##  NA's    :3
```

```r
print(unique(country_data$VAR))
```

```
## [1] "FLOOD_R_RP50_BUILT_SH"  "FLOOD_C_RP50_BUILT_SH"  "PWM_EX"
## [4]  "HD_POP_IND"              "FT_POP_IND"
```

```
#Cleaning the environment
bin <- c("country_flood_vf",
         "country_airpoll",
         "country_hotdays_fire",
         "country_flood",
         "flood",
         "TL2_keep",
         "country_code",
         "sum_country_flood")
rm(list=bin)
```

1.4 Combining countries and FUAs data

```
all_data <- bind_rows(FUA_data, country_data)
summary(all_data)
```

```
##    LOCATION              GEO                  TIME           VAR
##  Length:53300        Length:53300        Min.   :2001   Length:53300
##  Class :character    Class :character    1st Qu.:2006   Class :character
##  Mode  :character    Mode  :character    Median :2010   Mode  :character
##                                          Mean   :2010
##                                          3rd Qu.:2015
##                                          Max.   :2020
##
##      Value
## Min.    :  0.00 ##
1st Qu.:   0.00
## Median : 3.80 ##
Mean    :  22.92  ##
3rd Qu.: 16.90  ##
Max.    :366.00
##  NA's    :3
```

1.5 Treatment of missing data

```
NA_data <- all_data %>% filter(is.na(Value))
head(NA_data)
```

```
##   LOCATION GEO TIME                  VAR Value
## 1      BEL BEL 2004 FLOOD_C_RP50_BUILT_SH NA
## 2      BEL BEL 2007 FLOOD_C_RP50_BUILT_SH NA
## 3      BEL BEL 2020 FLOOD_C_RP50_BUILT_SH    NA
```

```
#There are three missing data for Belgium national level about its coastal food risk
#for 2004, 2007 and 2020.
#Not a problem for the overall index computation.
rm(list = c("NA_data", "bin"))
```

1.6 Treatment of values equal to 0

The data contains 37.255% of values equal to zero. They cannot bring information to build the index so we replace their value with 'NA' so they are ignored in the computation of the index.

```
mean(all_data$Value == 0, na.rm = TRUE)*100
```

```
## [1] 37.25538
```

```
zero_data <- all_data %>% filter(Value == 0)
summary(zero_data)
```

```
##     LOCATION              GEO                 TIME           VAR
##  Length:19856        Length:19856        Min.   :2001   Length:19856
##  Class :character    Class :character    1st Qu.:2005   Class :character
##  Mode  :character    Mode  :character    Median :2010   Mode  :character
##                                          Mean   :2010
##                                          3rd Qu.:2015
##                                          Max.   :2020
##      Value
## Min.  :0  ##
1st  Qu.:0  ##
Median :0
## Mean  :0 ##
3rd  Qu.:0  ##
Max.    :0
```

```
print(unique(zero_data$VAR))
```

```
## [1] "HEAT_STRESS_DAYS_UTCI32" "FIRES_POP_SH"
## [3] "FLOOD_R_RP50_BUILT_SH"   "FLOOD_C_RP50_BUILT_SH"
## [5] "HD_POP_IND"              "FT_POP_IND"
```

```
zero_data$TL <- ifelse(nchar(zero_data$GEO) == 3, "country", "FUA")
table(zero_data$TL)
```

```
##
## country     FUA
##     158   19698
```

```
count_GEO <-
  zero_data %>% group_by(LOCATION, TL, TIME, VAR) %>% summarise(n_TL = n())

only_zero_pairs <- zero_data %>%
                   group_by(GEO, VAR) %>%
                   summarise(n = n()) %>%
                   filter(n == length(period)) %>%
                   ungroup()
dim(only_zero_pairs)
```

```
## [1] 771   3
```

```
only_one <- c(length(period) - 1)
only_1_not_zero <- zero_data %>%
                        group_by(GEO, VAR) %>%
                        summarise(n = n()) %>%
                        filter(n == only_one) %>%
                        ungroup()
dim(only_1_not_zero)
```

```
## [1] 49  3
```

```
#Cleaning the environment
rm(list = c("zero_data", "count_GEO", "only_zero_pairs", "only_one", "only_1_not_zero"))

#Changing '0' values to 'NA' values
all_data_NA <- all_data %>% mutate(Value = if_else(Value == 0, NA, Value))
```

1.7 Description of the final database before index computation

```
summary(all_data_NA)
```

```
##    LOCATION              GEO                  TIME            VAR
##  Length:53300       Length:53300       Min.   :2001   Length:53300
##  Class :character   Class :character   1st Qu.:2006   Class :character
##  Mode  :character   Mode  :character   Median :2010   Mode  :character
##                                        Mean   :2010
##                                        3rd Qu.:2015
##                                        Max.   :2020
##
##      Value
## Min.   :  0.008 ##
1st Qu.:   5.600
## Median :  12.000
## Mean : 36.529 ##
3rd Qu.: 32.400 ##
Max.    :366.000
##  NA's    :19859
```

```
length(unique(all_data_NA$GEO))
```

```
## [1] 533
```

```
length(unique(all_data_NA$VAR))
```

```
## [1] 7
```

```
head(all_data_NA)
```

```
##     LOCATION    GEO  TIME     VAR Value
## 1          JPN  JPN18F  2001  PWM_EX 13.2
## 2          JPN  JPN18F  2002  PWM_EX13.2
## 3          JPN  JPN18F  2003  PWM_EX12.5
## 4          JPN  JPN18F  2004  PWM_EX12.4
## 5          JPN  JPN18F  2005  PWM_EX12.5
## 6          JPN  JPN18F  2006  PWM_EX12.9
```

2. Index computation

2.1 Preparation

```
#Computation of the evolution with a basis 100 on the first non-missing value for
#each GEO-VAR pairs
all_data_NA <- all_data_NA %>%
  arrange(GEO, VAR, TIME) %>%
  group_by(GEO, VAR) %>%
  mutate(Initial_Value = first(Value, order_by = TIME, na_rm = TRUE),
         Base_INDEX = Value / Initial_Value * 100)

#Computation of the Degradation of Environmental Performance Index for each GEO-TIME pairs
Grouped_DEPI <- all_data_NA %>%
  group_by(GEO, TIME) %>%
  summarise(Deterioration_EP_INDEX = psych::geometric.mean(Base_INDEX, na.rm = TRUE))

#Clear data frame with only relevant information
allFUAs_final_data <-
  merge(Grouped_DEPI, unique(all_data_NA[, c("LOCATION", "GEO")]), by = "GEO") %>%
  select(LOCATION, GEO, TIME, Deterioration_EP_INDEX)

#Cleaning the environment
bin <- c("FUA_data",
         "country_data",
         "all_data",
         "Grouped_DEPI")
rm(list=bin)
```

2.2 Finalisation

```
final_data <- allFUAs_final_data
final_data$TL <- ifelse(nchar(final_data$GEO) == 3, "Country", "FUA")

#Computation of the unique value for each year at the national and local level
final_data <- final_data %>%
  group_by(LOCATION, TL, TIME) %>%
  summarise(DEPI = mean(Deterioration_EP_INDEX, na.rm = TRUE)) %>%
  arrange(LOCATION, TIME)

summary(final_data)
```

```
##     LOCATION              TL                 TIME          DEPI
##  Length:400         Length:400         Min.   :2001   Min.   : 34.52
##  Class :character   Class :character   1st Qu.:2006   1st Qu.: 87.95
##  Mode  :character   Mode  :character   Median :2010   Median :100.00
##                                        Mean   :2010   Mean   :102.15
##                                        3rd Qu.:2015   3rd Qu.:114.23
##                                        Max.   :2020   Max.   :295.60
```

```
head(final_data)
```

```
## # A tibble: 6 x 4
## # Groups:   LOCATION, TL [2]
##   LOCATION TL       TIME  DEPI
##   <chr>    <chr>   <int> <dbl>
## 1 AUS      Country  2001 100
## 2 AUS      FUA      2001 100
## 3 AUS      Country  2002  83.9
## 4 AUS      FUA      2002 139.
## 5 AUS      Country  2003  97.7
## 6 AUS      FUA      2003 107.
```

```
summary(final_data$DEPI)
```

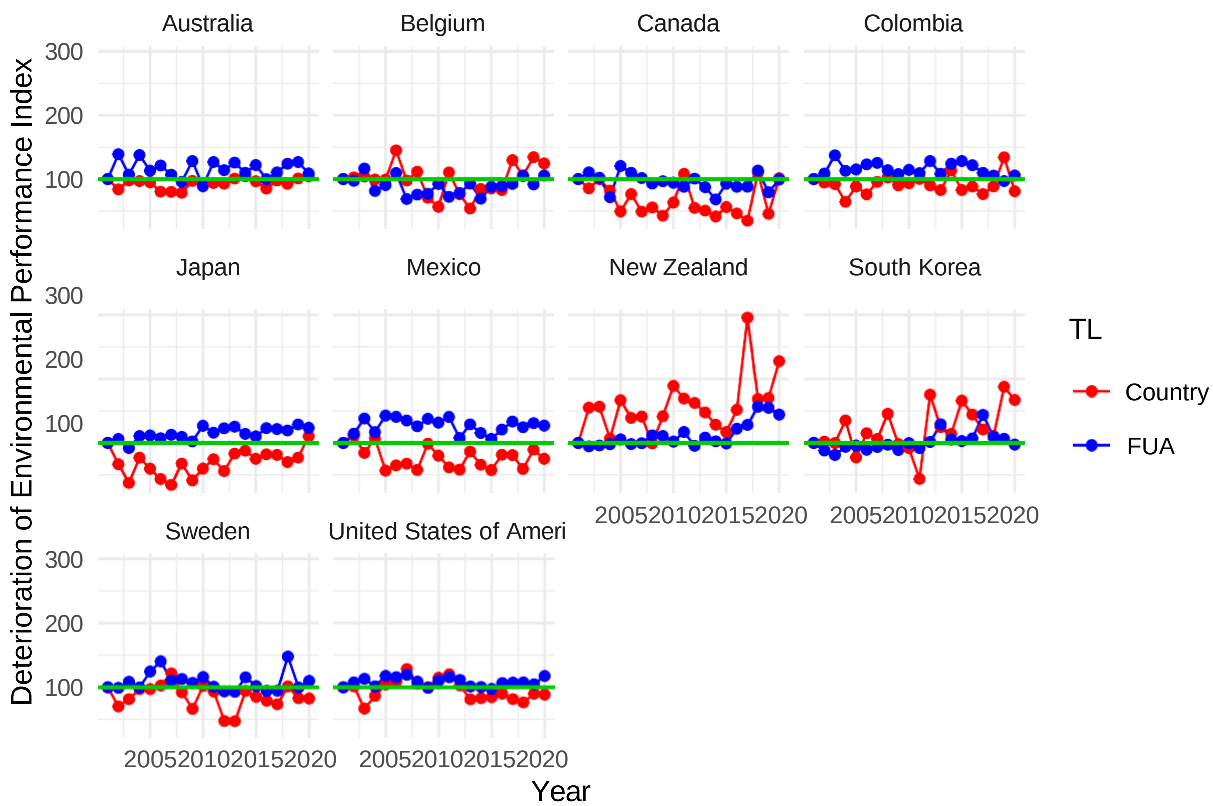
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   34.52   87.95  100.00  102.15  114.23  295.60
```

3. Results

3.1 By Country

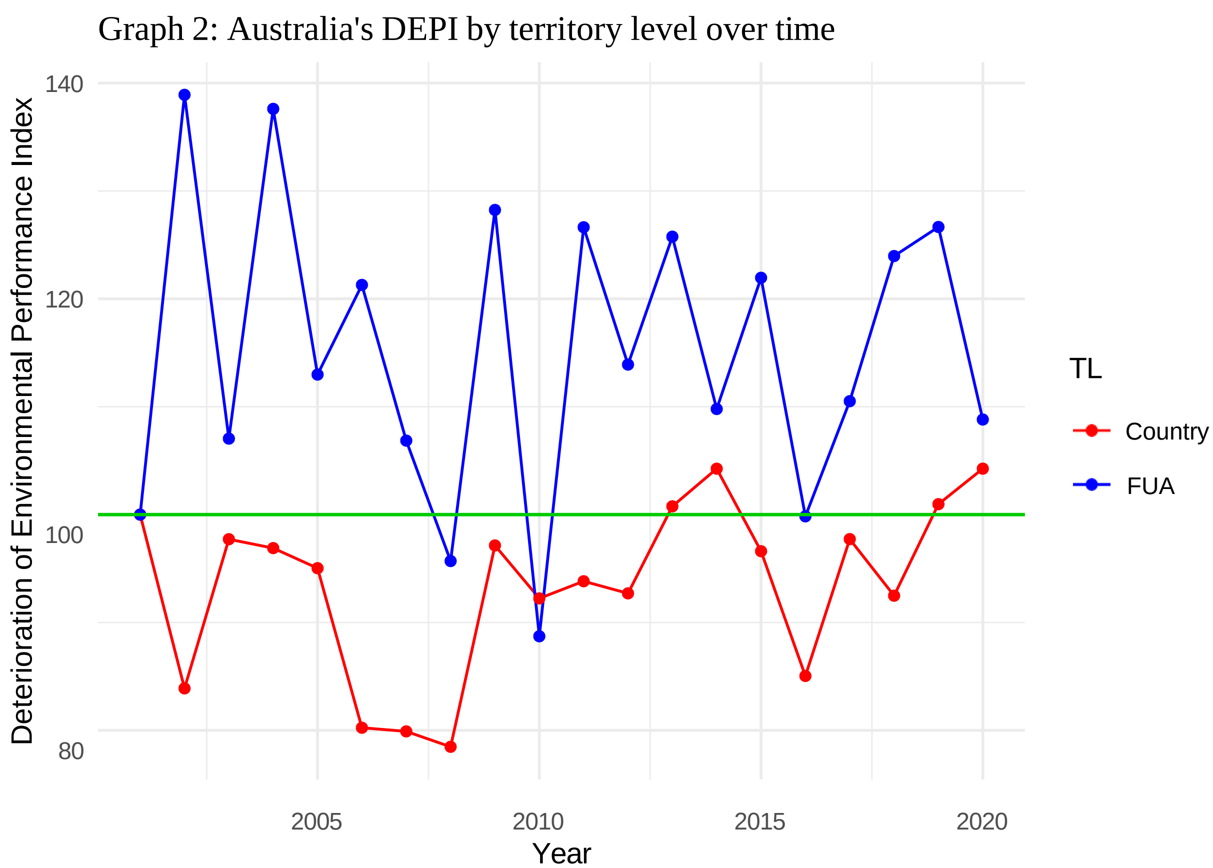
```
final_data <- final_data %>% mutate(LOCATION = recode(LOCATION, !!!country_name))

ggplot(final_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.75) +
  labs(title = "Graph 1: Deterioration of Environmental Performance over time by country and urban area
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  facet_wrap(~LOCATION) +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```

Graph 1: Deterioration of Environmental Performance over time by country



3.1.1 Australia

```
AUS_data <- final_data %>% filter(LOCATION == "Australia")

ggplot(AUS_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  labs(title = "Graph 2: Australia's DEPI by territory level over time",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```




```
AUS_data_loc <- AUS_data %>% filter(TL == "FUA")
AUS_data_nat <- AUS_data %>% filter(TL == "Country")
t.test(AUS_data_loc$DEPI,AUS_data_nat$DEPI, paired = T)
```

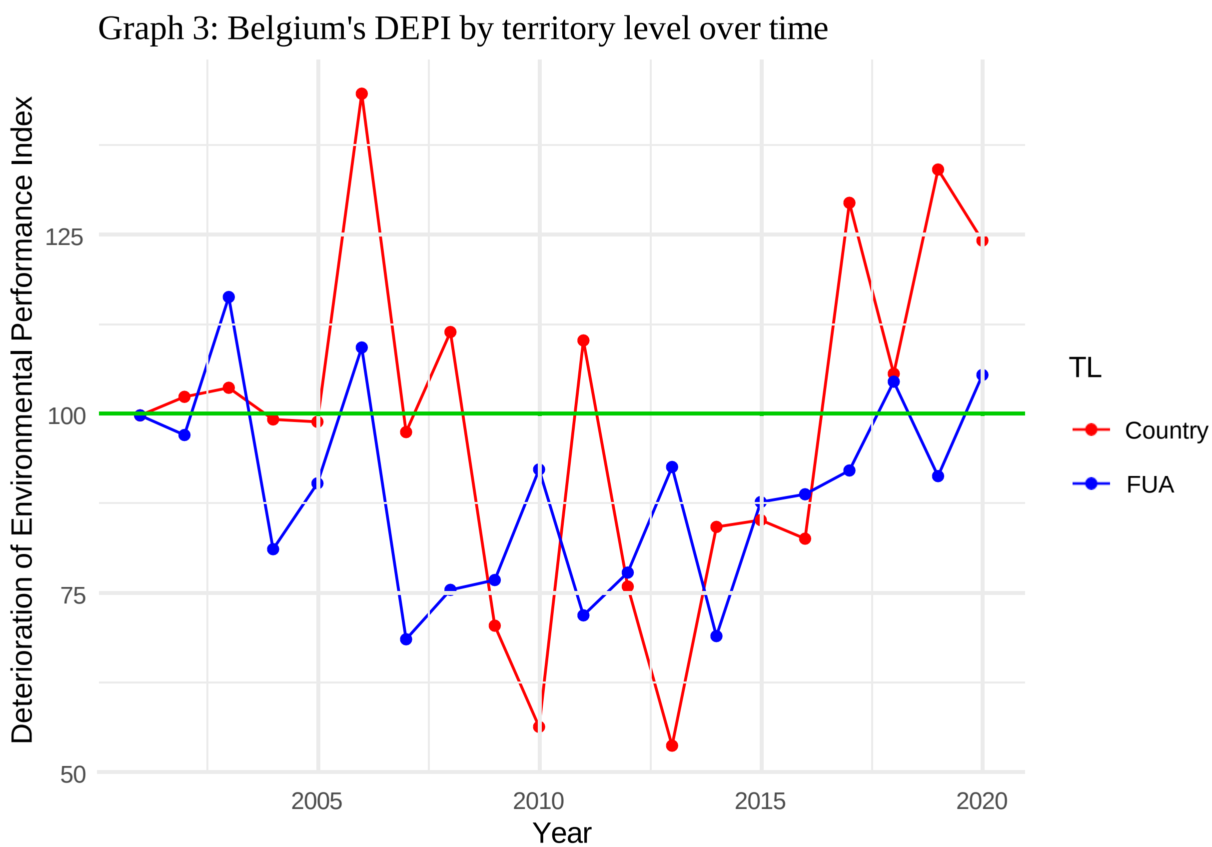
```
##
##  Paired t-test
##
## data:  AUS_data_loc$DEPI and AUS_data_nat$DEPI
## t = 6.5442, df = 19, p-value = 2.883e-06
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  14.79411 28.70706
## sample estimates:
## mean difference
##        21.75058
```

```
  #Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.2 Belgium

```
BEL_data <- final_data %>% filter(LOCATION == "Belgium")

ggplot(BEL_data, aes(x = TIME, y = DEPI, color = TL)) +
```

```
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  labs(title = "Graph 3: Belgium's DEPI by territory level over time",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```



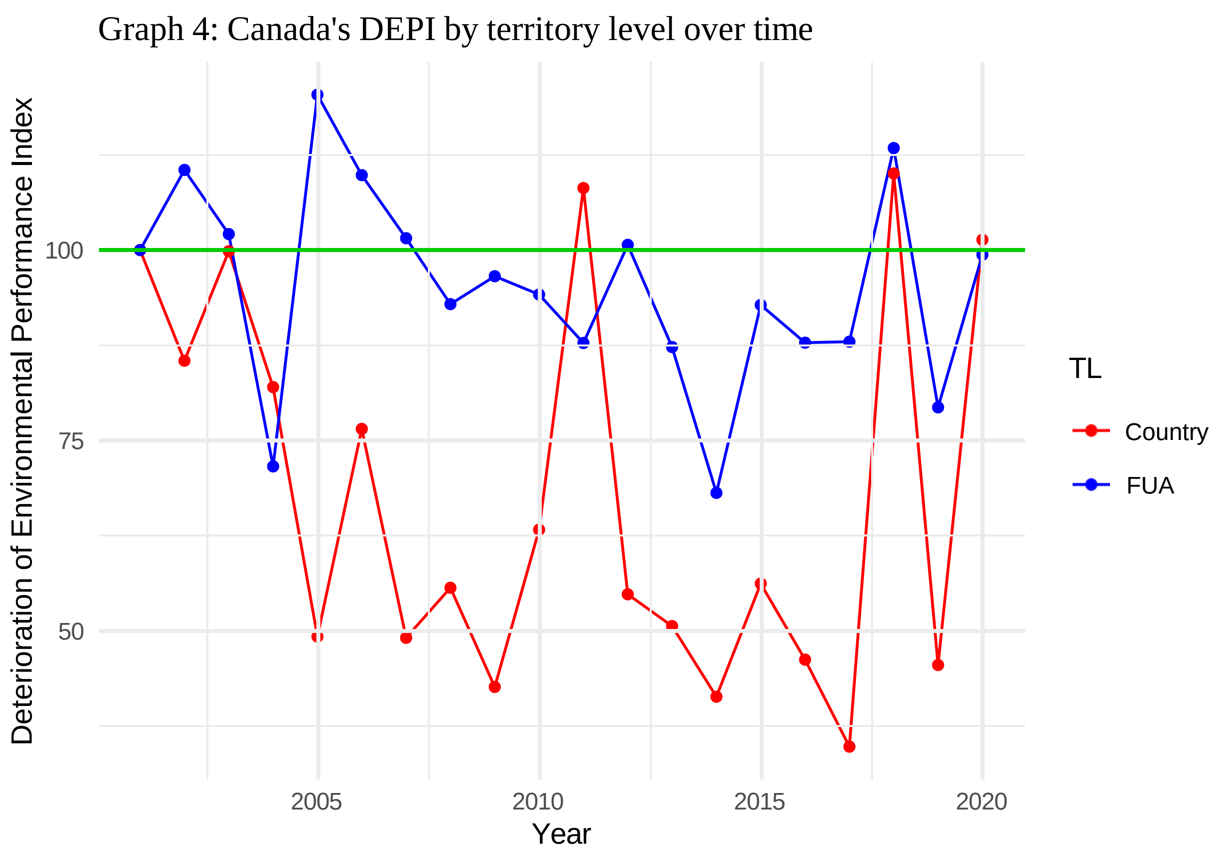

```
BEL_data_loc <- BEL_data %>% filter(TL == "FUA")
BEL_data_nat <- BEL_data %>% filter(TL == "Country")
t.test(BEL_data_loc$DEPI,BEL_data_nat$DEPI, paired = T)
```

```
##
##  Paired t-test
##
## data:  BEL_data_loc$DEPI and BEL_data_nat$DEPI
## t = -1.7253, df = 19, p-value = 0.1007
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  -20.069045   1.932604
## sample estimates:
## mean difference
##       -9.068221
```

```
#Based on this result, we shall accept the null hypothesis of no difference.
```

3.1.3 Canada

```
CAN_data <- final_data %>% filter(LOCATION == "Canada")

ggplot(CAN_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  labs(title = "Graph 4: Canada's DEPI by territory level over time",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```




```
CAN_data_loc <- CAN_data %>% filter(TL == "FUA")
CAN_data_nat <- CAN_data %>% filter(TL == "Country")
t.test(CAN_data_loc$DEPI,CAN_data_nat$DEPI, paired = T)
```

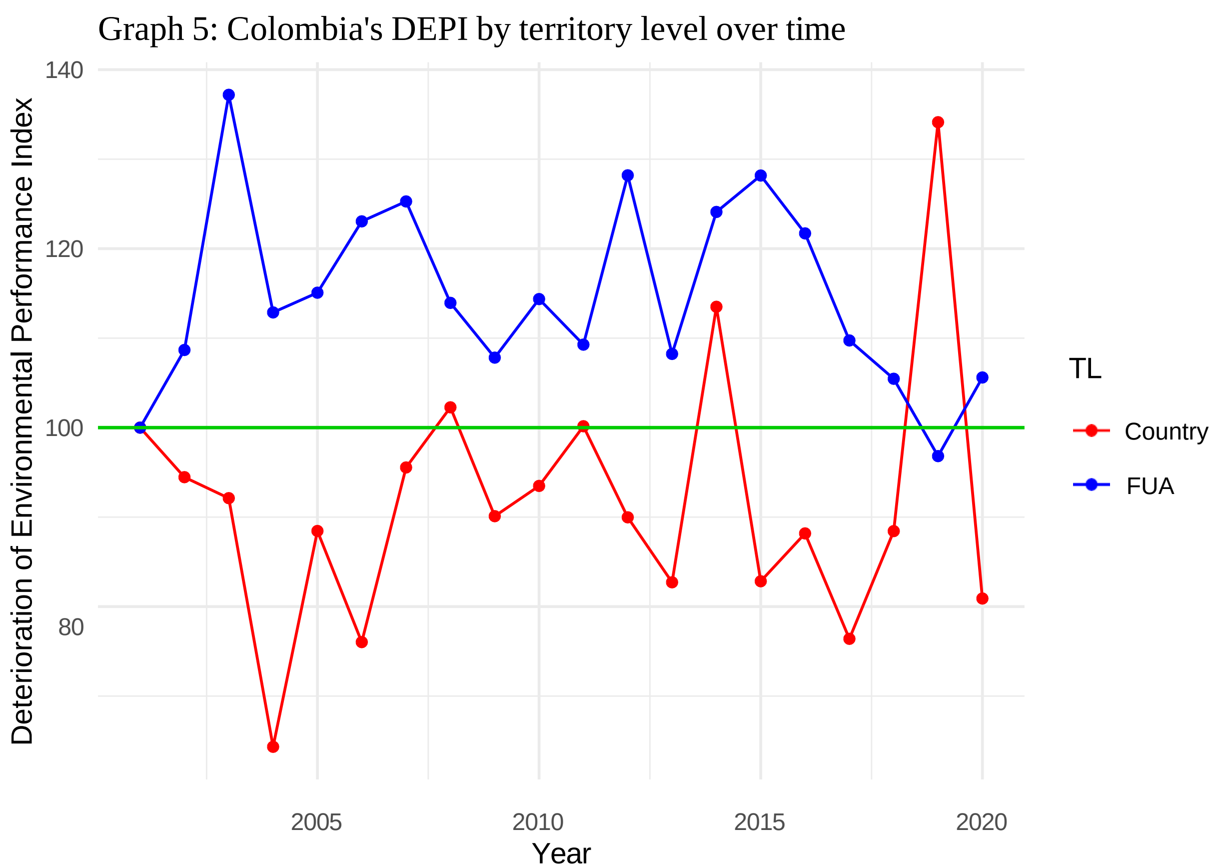
```
##
##  Paired t-test
```

```
##
## data:  CAN_data_loc$DEPI and CAN_data_nat$DEPI
## t = 5.0449, df = 19, p-value = 7.192e-05
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  16.13559 39.01709
## sample estimates:
## mean difference
##        27.57634
```

```
#Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.4 Colombia

```
COL_data <- final_data %>% filter(LOCATION == "Colombia")

ggplot(COL_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  labs(title = "Graph 5: Colombia's DEPI by territory level over time",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```




```
COL_data_loc <- COL_data %>% filter(TL == "FUA")
COL_data_nat <- COL_data %>% filter(TL == "Country")
t.test(COL_data_loc$DEPI,COL_data_nat$DEPI, paired = T)
```

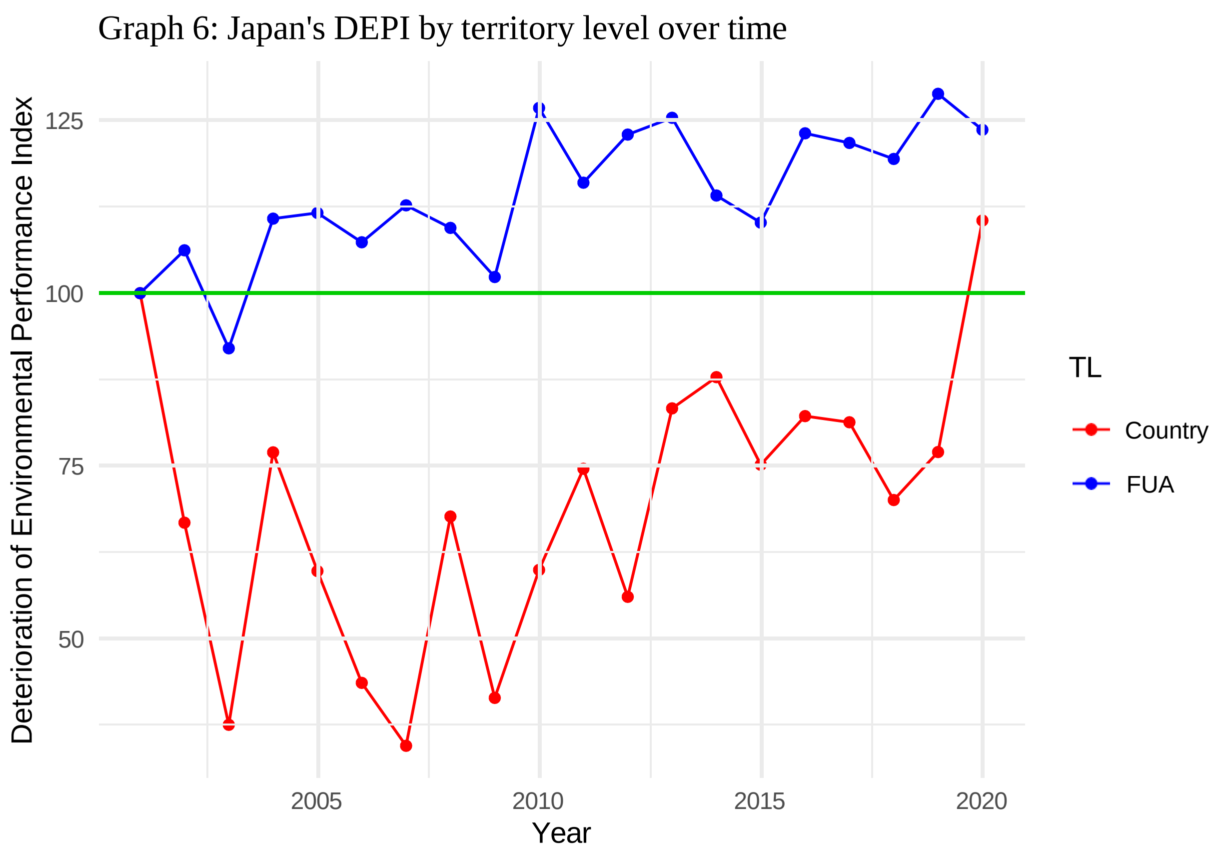
```
##
##  Paired t-test
##
## data:  COL_data_loc$DEPI and COL_data_nat$DEPI
## t = 5.188, df = 19, p-value = 5.233e-05
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  13.7677 32.3888
## sample estimates:
## mean difference
##        23.07825
```

```
#Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.5 Japan

```
JPN_data <- final_data %>% filter(LOCATION == "Japan")

ggplot(JPN_data, aes(x = TIME, y = DEPI, color = TL)) +
```

```
geom_line() +
geom_point() +
geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
labs(title = "Graph 6: Japan's DEPI by territory level over time",
     x = "Year",
     y = "Deterioration of Environmental Performance Index") +
theme_minimal() +
scale_color_manual(values = c("#FF0000", "#0000FF"))
```



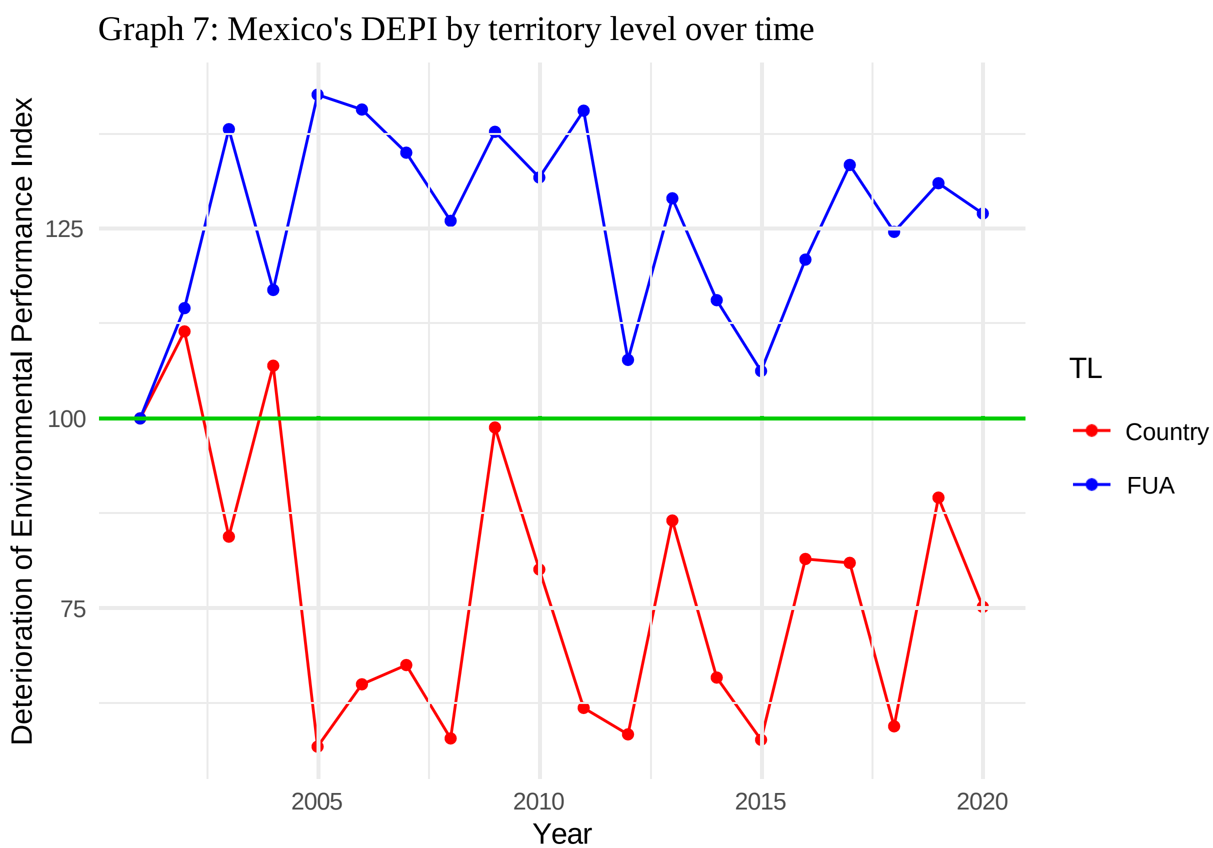

```
JPN_data_loc <- JPN_data %>% filter(TL == "FUA")
JPN_data_nat <- JPN_data %>% filter(TL == "Country")
t.test(JPN_data_loc$DEPI,JPN_data_nat$DEPI, paired = T)
```

```
##
##  Paired t-test
##
## data:  JPN_data_loc$DEPI and JPN_data_nat$DEPI
## t = 10.792, df = 19, p-value = 1.521e-09
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  36.19539 53.61295
## sample estimates:
## mean difference
##        44.90417
```

```
#Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.6 Mexico

```
MEX_data <- final_data %>% filter(LOCATION == "Mexico")

ggplot(MEX_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  labs(title = "Graph 7: Mexico's DEPI by territory level over time",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```




```
MEX_data_loc <- MEX_data %>% filter(TL == "FUA")
MEX_data_nat <- MEX_data %>% filter(TL == "Country")
t.test(MEX_data_loc$DEPI,MEX_data_nat$DEPI, paired = T)
```

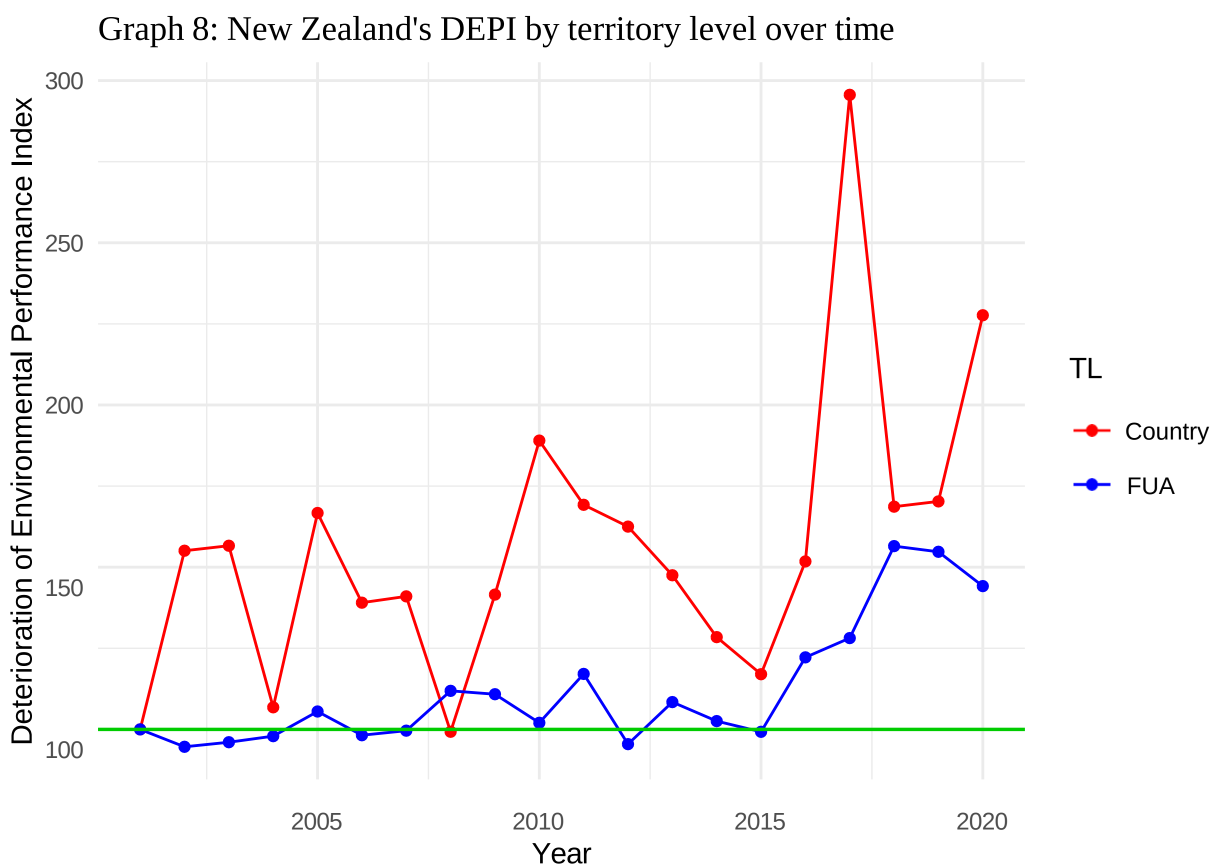
```
##
##   Paired t-test
```

```
##
## data:  MEX_data_loc$DEPI and MEX_data_nat$DEPI
## t = 9.3508, df = 19, p-value = 1.534e-08
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  37.75588 59.53232
## sample estimates:
## mean difference
##         48.6441
```

```
#Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.7 New Zealand

```
NZL_data <- final_data %>% filter(LOCATION == "New Zealand")

ggplot(NZL_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  labs(title = "Graph 8: New Zealand's DEPI by territory level over time",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```




```
NZL_data_loc <- NZL_data %>% filter(TL == "FUA")
NZL_data_nat <- NZL_data %>% filter(TL == "Country")
t.test(NZL_data_loc$DEPI,NZL_data_nat$DEPI, paired = T)
```

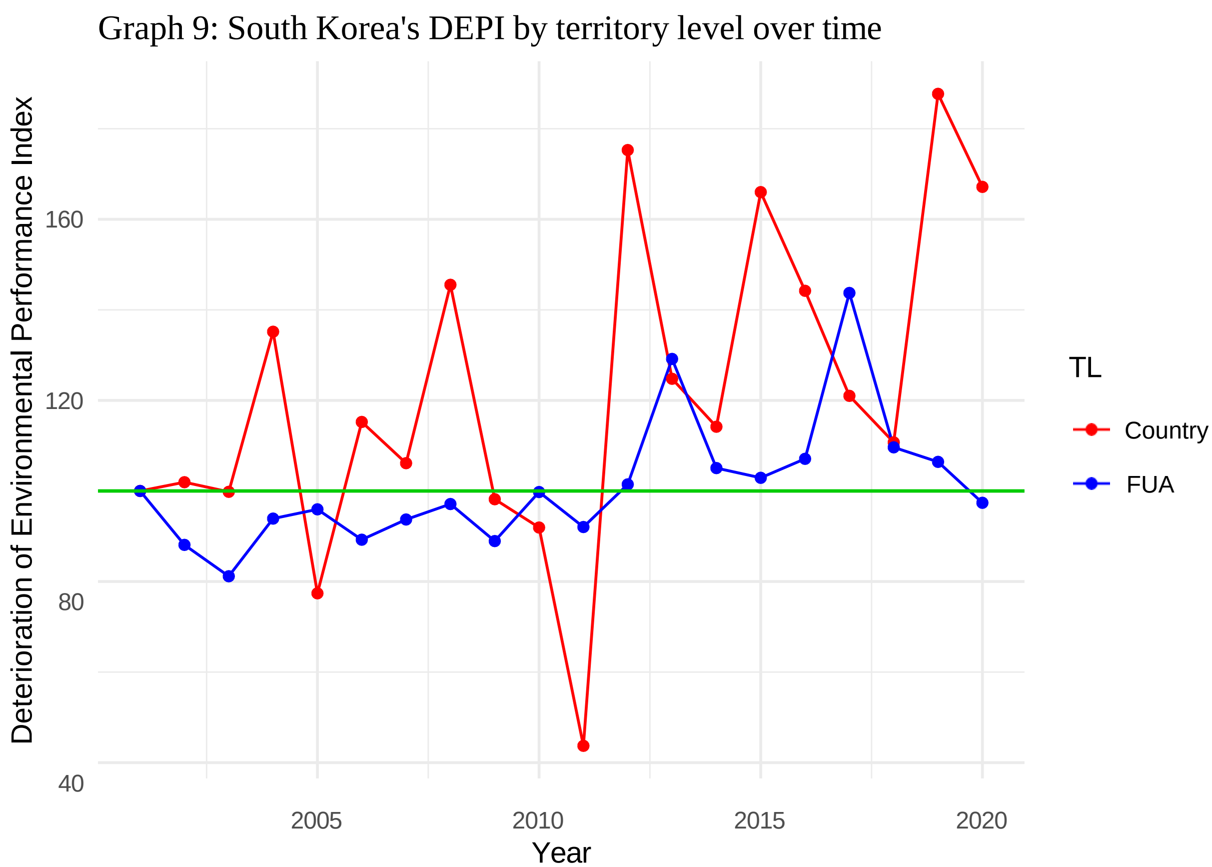
```
##  Paired t-test
##
## data:  NZL_data_loc$DEPI and NZL_data_nat$DEPI
## t = -5.0235, df = 19, p-value = 7.543e-05
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  -62.93885 -25.91748
## sample estimates:
## mean difference
##         -44.42816
```

```
#Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.8 South Korea

```
KOR_data <- final_data %>% filter(LOCATION == "South Korea")

ggplot(KOR_data, aes(x = TIME, y = DEPI, color = TL)) +
```

```
geom_line() +
geom_point() +
geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
labs(title = "Graph 9: South Korea's DEPI by territory level over time",
     x = "Year",
     y = "Deterioration of Environmental Performance Index") +
theme_minimal() +
scale_color_manual(values = c("#FF0000", "#0000FF"))
```



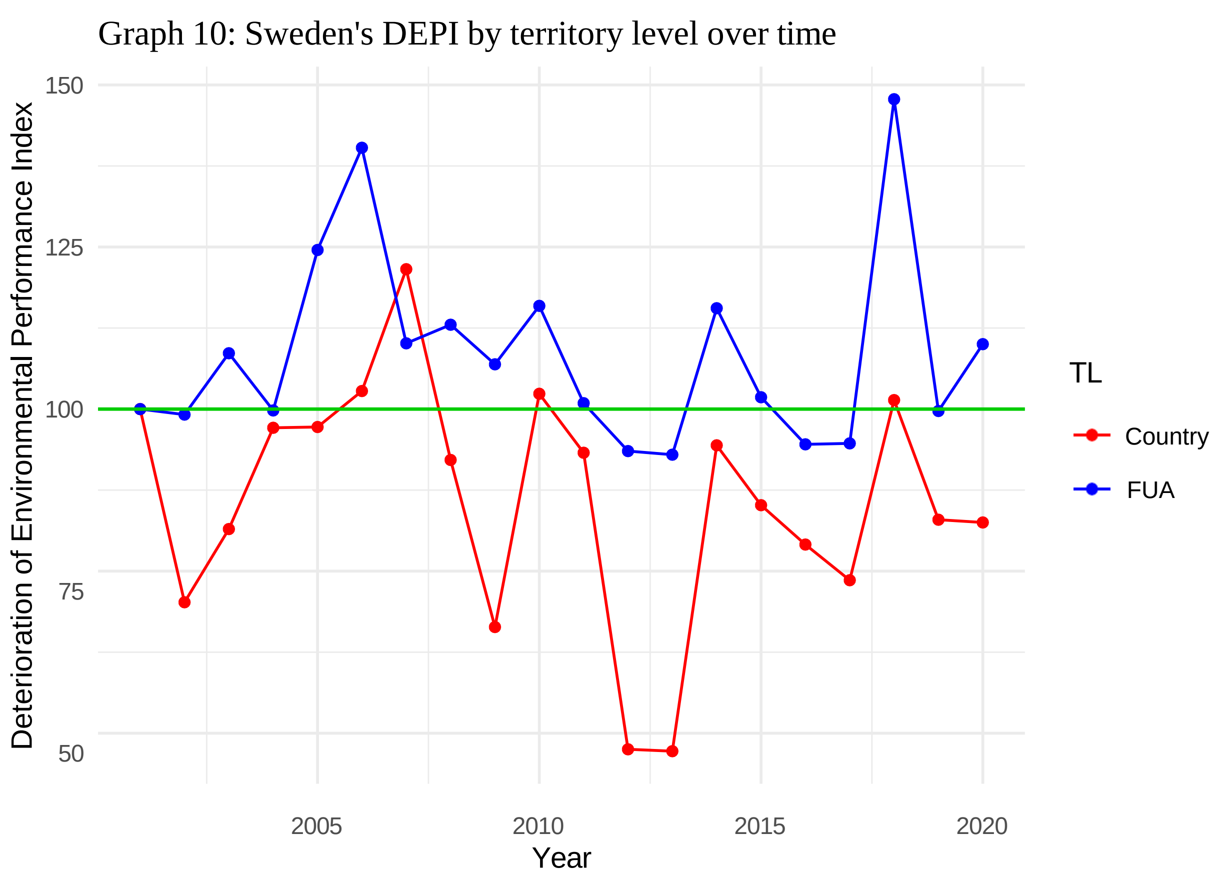

```
KOR_data_loc <- KOR_data %>% filter(TL == "FUA")
KOR_data_nat <- KOR_data %>% filter(TL == "Country")
t.test(KOR_data_loc$DEPI,KOR_data_nat$DEPI, paired = T )
```

```
##   Paired t-test
##
## data:   KOR_data_loc$DEPI and KOR_data_nat$DEPI
## t = -2.5917, df = 19, p-value = 0.0179
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  -36.455215  -3.880524
## sample estimates:
## mean difference
##        -20.16787
```

```
#Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.9 Sweden

```
SWE_data <- final_data %>% filter(LOCATION == "Sweden")

ggplot(SWE_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  labs(title = "Graph 10: Sweden's DEPI by territory level over time",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```



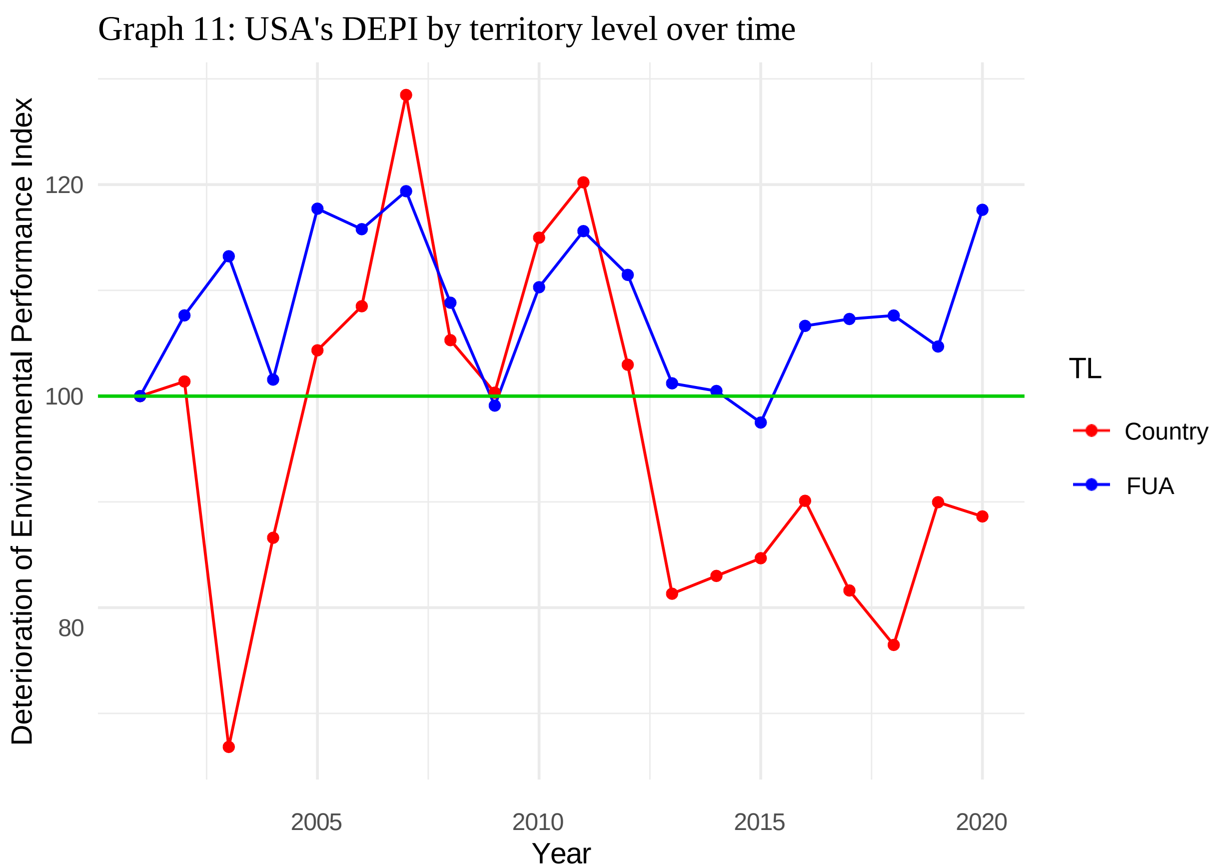

```
SWE_data_loc <- SWE_data %>% filter(TL == "FUA")
SWE_data_nat <- SWE_data %>% filter(TL == "Country")
t.test(SWE_data_loc$DEPI,SWE_data_nat$DEPI, paired = T )

##
##  Paired t-test
```

```
##
## data:  SWE_data_loc$DEPI and SWE_data_nat$DEPI
## t = 6.3521, df = 19, p-value = 4.286e-06
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  15.13738 30.01514
## sample estimates:
## mean difference
##        22.57626
```

```
#Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.10 United States of America

```
USA_data <- final_data %>% filter(LOCATION == "United States of America")

ggplot(USA_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  labs(title = "Graph 11: USA's DEPI by territory level over time",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```




```
USA_data_loc <- USA_data %>% filter(TL == "FUA")
USA_data_nat <- USA_data %>% filter(TL == "Country")
t.test(USA_data_loc$DEPI,USA_data_nat$DEPI, paired = T )
```

```
##
##  Paired t-test
##
## data:  USA_data_loc$DEPI and USA_data_nat$DEPI
## t = 4.0223, df = 19, p-value = 0.0007281
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##   5.947506 18.852072
## sample estimates:
## mean difference
##        12.39979
```

```
#Based on this result, we shall reject the null hypothesis of no difference.
```

3.1.11 Paired t-test to investigate a possible common continent effect

```
#Asia
t.test(JPN_data_nat$DEPI, KOR_data_nat$DEPI, paired = T)
```

```
##
##   Paired t-test
##
## data:  JPN_data_nat$DEPI and KOR_data_nat$DEPI
## t = -6.584, df = 19, p-value = 2.657e-06
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  -68.50440 -35.45573
## sample estimates:
## mean difference
##       -51.98006
```

```
t.test(JPN_data_loc$DEPI, KOR_data_loc$DEPI, paired = T)
```

```
##
##   Paired t-test
##
## data:  JPN_data_loc$DEPI and KOR_data_loc$DEPI
## t = 5.0927, df = 19, p-value = 6.466e-05
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##   7.711384 18.472565
## sample estimates:
## mean difference
##        13.09197
```

```
  #Based on these results, we shall reject the null hypothesis of no difference.

#Europe
t.test(BEL_data_nat$DEPI, SWE_data_nat$DEPI, paired = T)
```

```
##
##   Paired t-test
##
## data:  BEL_data_nat$DEPI and SWE_data_nat$DEPI
## t = 2.2745, df = 19, p-value = 0.03472
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##   1.018333 24.507841
## sample estimates:
## mean difference
##        12.76309
```

```
t.test(BEL_data_loc$DEPI, SWE_data_loc$DEPI, paired = T)
```

```
##
##   Paired t-test
##
## data:  BEL_data_loc$DEPI and SWE_data_loc$DEPI
## t = -5.0442, df = 19, p-value = 7.204e-05
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
```

```
##   -26.71605 -11.04673
## sample estimates:
## mean difference
##         -18.88139
```

```
#Based on these results, we shall reject the null hypothesis of no difference.

#North America
t.test(CAN_data_nat$DEPI, USA_data_nat$DEPI, paired = T)
```

```
##
##  Paired t-test
##
## data:  CAN_data_nat$DEPI and USA_data_nat$DEPI
## t = -4.1259, df = 19, p-value = 0.0005747
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##   -42.43276 -13.87062
## sample estimates:
## mean difference
##         -28.15169
```

```
t.test(CAN_data_loc$DEPI, USA_data_loc$DEPI, paired = T)
```

```
##
##  Paired t-test
##
## data:  CAN_data_loc$DEPI and USA_data_loc$DEPI
## t = -5.1253, df = 19, p-value = 6.014e-05
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##   -18.273791  -7.676484
## sample estimates:
## mean difference
##         -12.97514
```

```
#Based on these results, we shall reject the null hypothesis of no difference.

#Oceania
t.test(AUS_data_nat$DEPI, NZL_data_nat$DEPI, paired = T)
```

```
##
##  Paired t-test
##
## data:  AUS_data_nat$DEPI and NZL_data_nat$DEPI
## t = -6.4832, df = 19, p-value = 3.268e-06
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##   -83.57570 -42.78252
## sample estimates:
## mean difference
##         -63.17911
```

```
t.test(AUS_data_loc$DEPI, NZL_data_loc$DEPI, paired = T)
```

```
##
##  Paired t-test
##
## data:  AUS_data_loc$DEPI and NZL_data_loc$DEPI
## t = 0.58276, df = 19, p-value = 0.5669
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  -7.773721 13.772995
## sample estimates:
## mean difference
##        2.999637
```

```
#Australia and New Zealand show different results for paired t-tests.

#South America
t.test(COL_data_nat$DEPI, MEX_data_nat$DEPI, paired = T)
```

```
##
##  Paired t-test
##
## data:  COL_data_nat$DEPI and MEX_data_nat$DEPI
## t = 2.7456, df = 19, p-value = 0.01286
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##   3.422068 25.373008
## sample estimates:
## mean difference
##        14.39754
```

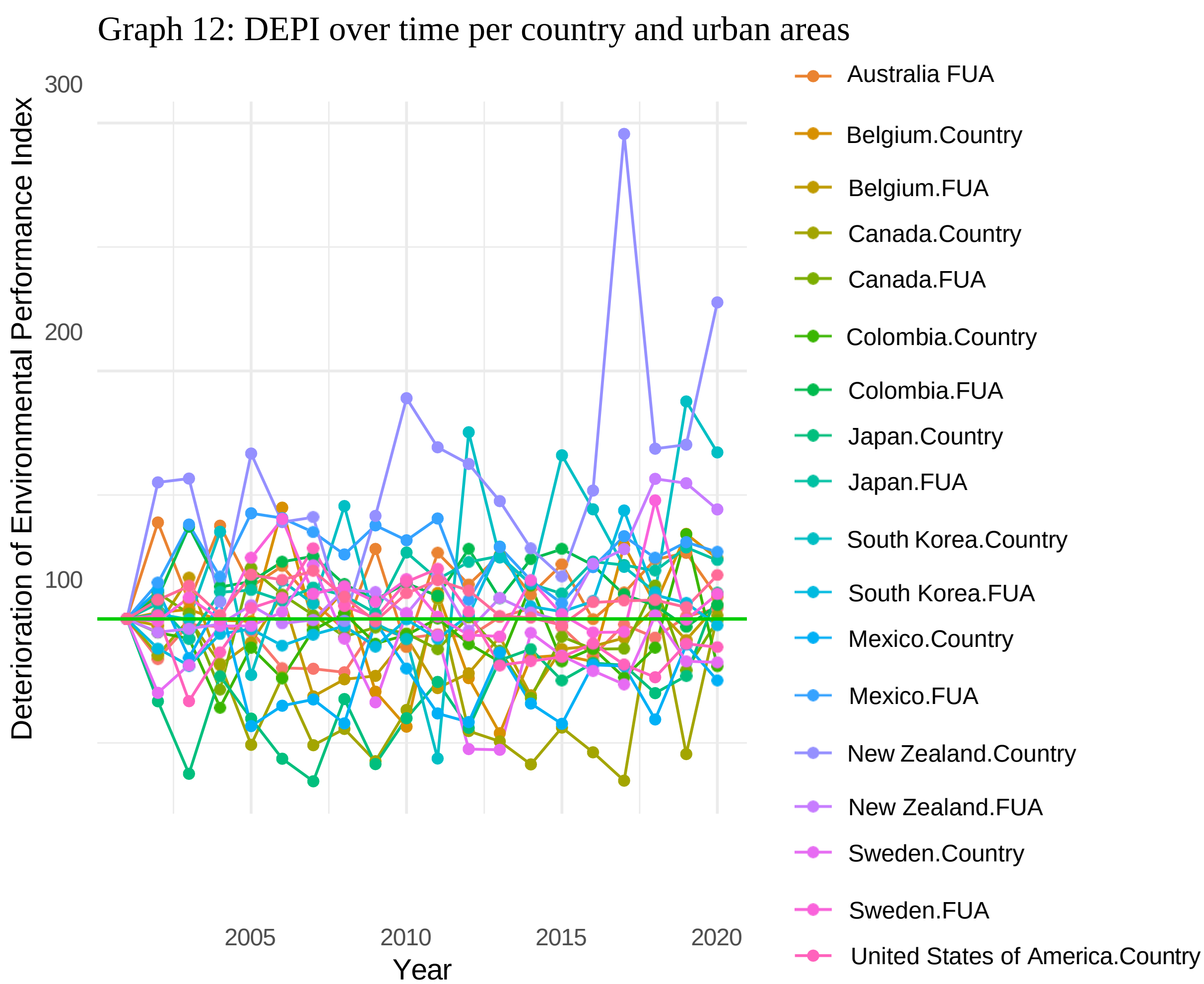
```
t.test(COL_data_loc$DEPI, MEX_data_loc$DEPI, paired = T)
```

```
##
##  Paired t-test
##
## data:  COL_data_loc$DEPI and MEX_data_loc$DEPI
## t = -3.0834, df = 19, p-value = 0.006117
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  -18.749403  -3.587218
## sample estimates:
## mean difference
##       -11.16831
```

```
#Based on these results, we shall reject the null hypothesis of no difference.
```

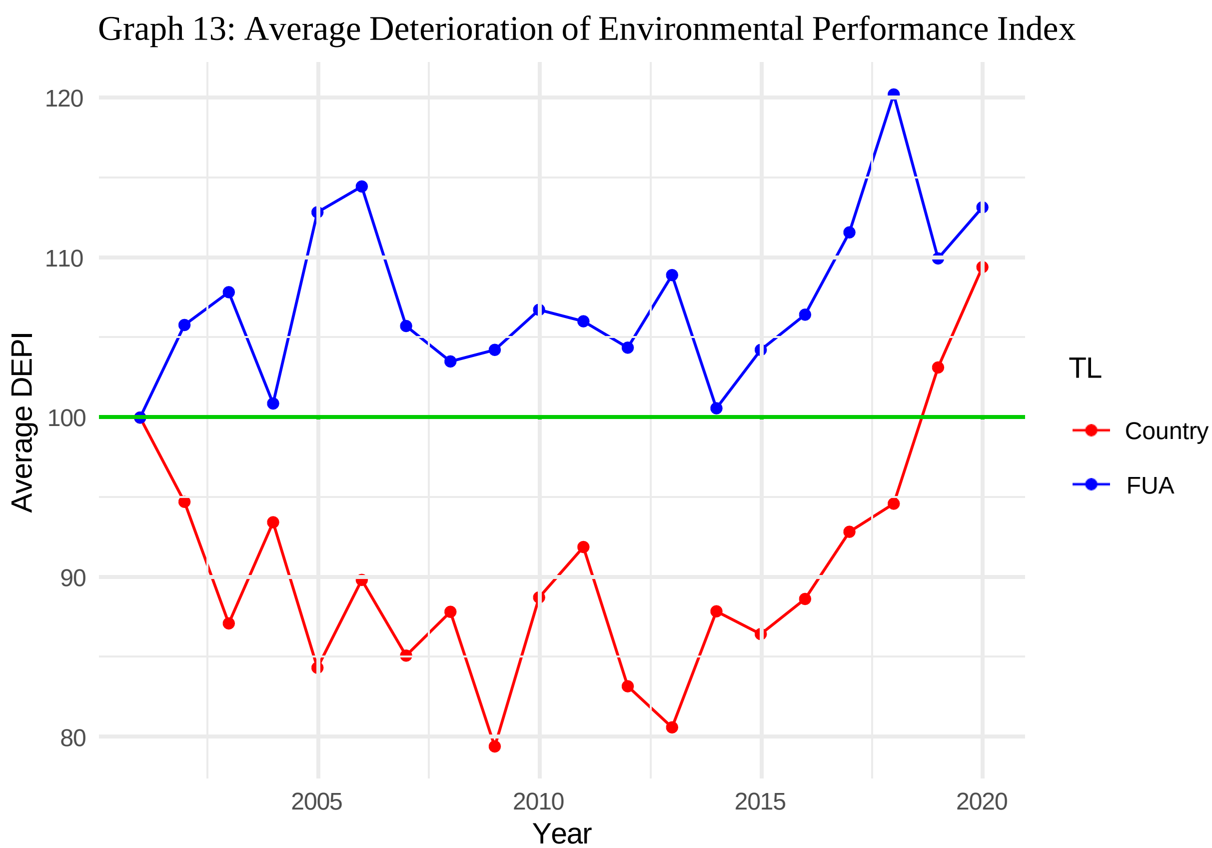
3.2 All together in the same plot

```r
final_data$LOCATION_TL <- interaction(final_data$LOCATION, final_data$TL)
final_data$LOCATION_TL <- forcats::fct_inorder(final_data$LOCATION_TL)


ggplot(final_data, aes(x = TIME, y = DEPI, group = LOCATION_TL, color = LOCATION_TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +
  theme_minimal() +
  labs(title = "Graph 12: DEPI over time per country and urban areas level", x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  theme(legend.title = element_blank())
```



3.3 Comparative analysis between the local and national levels

```
geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.6) +

local_vs_national <- final_data %>%
  group_by(TL, TIME) %>%
  summarise(avg_DEPI = psych::geometric.mean(DEPI, na.rm = TRUE))


ggplot(local_vs_national, aes(x = TIME, y = avg_DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  labs(title = "Graph 13: Average Deterioration of Environmental Performance Index by territory level",
       x = "Year",
       y = "Average DEPI") +
  theme_minimal()+
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```



```
#Paired sample t-test
All_local_data <- local_vs_national %>% filter(TL == "FUA")
All_nat_data <- local_vs_national %>% filter(TL == "Country")
t.test(All_local_data$avg_DEPI, All_nat_data$avg_DEPI, paired = T)
```

```
##  Paired t-test
##
## data:  All_local_data$avg_DEPI and All_nat_data$avg_DEPI
## t = 9.4134, df = 19, p-value = 1.381e-08
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  13.14801 20.66647
## sample estimates:
## mean difference
##        16.90724
```

```
  #Means of DEPI results for each level are statistically different with
```

```
#Cleaning the environment
all_pattern <- c("^AUS_data",
                 "^BEL_data",
                 "^CAN_data",
                 "^COL_data",
                 "^JPN_data",
                 "^KOR_data",
                 "^MEX_data",
                 "^NZL_data",
                 "^SWE_data",
                 "^USA_data",
                 "local_vs_national",
                 "All_local_data",
                 "All_nat_data",
                 "all_pattern")
all_pattern <- paste(all_pattern, collapse = "|")
bin_data <- ls(pattern = all_pattern)
rm(list=bin_data)
```

4. Robustness analysis

Due to the importance of flood risks driving country results, we test the computation of the index without including those outcomes.

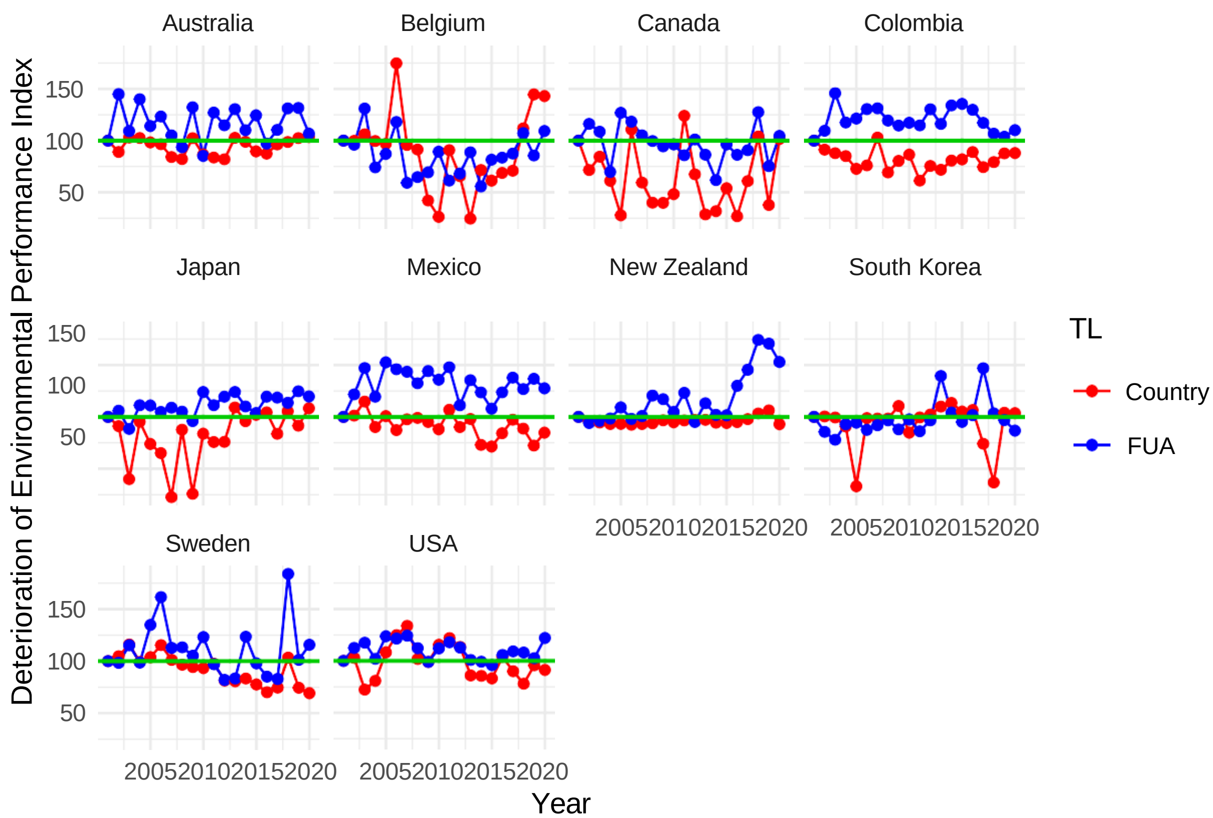
```
#Removing flood information from the data
not_flood <- c("FLOOD_C_RP50_BUILT_SH", "FLOOD_R_RP50_BUILT_SH")
test_all_data <- all_data_NA %>% filter(!(VAR %in% not_flood))

#Removing the share of the population exposed to wildfires in New Zealand as it expands

# too much of the graphical result scale, making it unreadable
test_all_data$Base_INDEX[test_all_data$GEO == "NZL" & test_all_data$VAR == "FT_POP_IND"] <- NA
```

```r
#Removing the share of population expose to hot days in South Korea as it expands to much

# the graphical result scale, making it unreadable
test_all_data$Base_INDEX[test_all_data$GEO == "KOR" & test_all_data$VAR == "HD_POP_IND"] <- NA

#Computation of the Degradation of Environmental Performance Index for each GEO-TIME pairs
Grouped_DEPI2 <- test_all_data %>%
  group_by(GEO, TIME) %>%
  summarise(Deterioration_EP_INDEX = psych::geometric.mean(Base_INDEX, na.rm = TRUE))

#Clear data frame with only relevant information
DEPI_test_data <-
  merge(Grouped_DEPI2, unique(test_all_data[, c("LOCATION", "GEO")]), by = "GEO") %>%
  select(LOCATION, GEO, TIME, Deterioration_EP_INDEX)

DEPI_test_data$TL <- ifelse(nchar(DEPI_test_data$GEO) == 3, "Country", "FUA")

#Computation of the unique value for each year at the national and local level
DEPI_test_data <- DEPI_test_data %>%
  group_by(LOCATION, TL, TIME) %>%
  summarise(DEPI = mean(Deterioration_EP_INDEX, na.rm = TRUE)) %>%
  arrange(LOCATION, TIME)

summary(DEPI_test_data)
```

```
##    LOCATION              TL                 TIME           DEPI
##  Length:400         Length:400         Min.   :2001   Min.   : 22.62
##  Class :character   Class :character   1st Qu.:2006   1st Qu.: 87.35
##  Mode  :character   Mode  :character   Median :2010   Median : 99.89
##                                        Mean   :2010   Mean   : 99.18
##                                        3rd Qu.:2015   3rd Qu.:111.92
##                                        Max.   :2020   Max.   :183.93
```

```r
#Plotting the results
DEPI_test_data <- DEPI_test_data %>% mutate(LOCATION = recode(LOCATION, !!!country_name))

ggplot(DEPI_test_data, aes(x = TIME, y = DEPI, color = TL)) +
  geom_line() +
  geom_point() +
  geom_hline(yintercept = 100, color = "#00CC00", linewidth = 0.75) +
  labs(title = "Graph 14: Alternative DEPI over time by country and urban areas level",
       x = "Year",
       y = "Deterioration of Environmental Performance Index") +
  facet_wrap(~LOCATION) +
  theme_minimal() +
  scale_color_manual(values = c("#FF0000", "#0000FF"))
```

Graph 14: Alternative DEPI over time by country and urban areas level



Last clean up

```
rm(list = ls())
cat("\014")
```

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