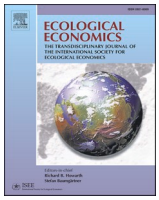
Ecological Economics 227 (2025) 108416



Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon





Impacts of population, affluence and urbanization on local air pollution and land transformation – A regional STIRPAT analysis for German districts

Johannes Lohwasser [a,*], Thomas Bolognesi [b], Axel Schaffer [a]

[a] Bundeswehr University Munich, Germany
[b] Grenoble Ecole de Management, France

ARTICLE INFO

Keywords:
STIRPAT
NO_x emissions
Soil sealing
Environmental elasticities
Environmental Kuznets Curve
Regional environmental indicators

ABSTRACT

Anthropogenic environmental impacts substantially threaten the sustainable development of cities and counties. This paper offers an original assessment of the role played by population, economic growth and technology change in the evolution of local air pollution and soil sealing, using the STIRPAT approach. The analysis covers the development of 367 German counties and autonomous cities (NUTS 3 level) between 1990 and 2020. Results indicate that the development of NO_x emissions and soil sealing is clearly related to car ownership, number of houses and regional population for all counties. In contrast to, environmental impacts related to GDP per capita, share of industrial manufacturing and urban density depend on the types of regions. Finally, results show non-linear (EKC) dynamics regarding the impacts of population and GDP per capita on NO_x emissions. Environmental policies need to take care about the settlement structures and the level of relevant variables.

1. Introduction

According to the latest update of the planetary boundary framework six of nine boundaries are already transgressed. Accordingly, Richardson et al. (2023) conclude that anthropogenic activities place "unprecedented pressure on the Earth system" and significantly reduce ecological resilience when the planet needs it the most. Though the framework cannot be directly transferred to a local scale, biodiversity loss, carbon emissions, air pollution, changing land-use pattern etc. largely originate at regional level and are closely related to local economic, demographic and geographic structure (Rees and Wackernagel, 2008; Seto et al., 2012). Anthropogenic activities in the cities, for example, account for about three-quarter of global GHG emissions (IPCC, 2014), are largely responsible for air pollution, and significantly contribute to the over-consumption of natural resources. In addition, we observe strong and severe impacts on biosphere integrity and biogeochemical flows from agricultural production in rural regions.

In conclusion successful sustainability transitions do not only rely on international commitments and institutional arrangements, but also demand for an effective implementation of related policies at regional level. It is therefore of particular interest to extend the global and national sustainability analyses to the regional level. This does not (only) mean to break down global measures at local level. Rather the field of interest widens and goes beyond global issues such as climate change (which, of course remains of particular concern). Accordingly, empirical studies at regional level increasingly consider sustainability indicators aside from CO_2 emissions.

One indicator is nitrogen oxide (NO_x), which does not only reflect air pollution and human health effects but can (due to its comparatively short atmospheric lifetime) further be considered a good measure for local and contemporary combustion as argued by Shaw and Van Heyst (2022). Thus, in comparison with greenhouse gases (which have a long atmospheric lifetime and can hardly be attributed to local activities) NO_x emissions are more likely to have an (immediate) impact on the region where they are produced. De- or increasing concentrations are therefore a good indicator of successful or unsuccessful efforts of decarbonization at local level.

Another important indicator for human influence on the local environment is land transformation and in particular soil sealing. Increasing demand for built up area within but also outside the cities does not only interrupt with the multiple ecological functions of soil (e.g. resource, filter or habitat functions) but further enhances the danger of flooding in exposed regions and the risk of heat islands in urban areas.

While NO_x emissions and soil sealing affect the regions in different ways (and could easily be considered separately), empirical findings so far indicate that both indicators are driven by similar anthropogenic

* Corresponding author.
E-mail addresses: johannes.lohwasser@unibw.de (J. Lohwasser), thomas.bolognesi@grenoble-em.com (T. Bolognesi), axel.schaffer@unibw.de (A. Schaffer).

https://doi.org/10.1016/j.ecolecon.2024.108416
Received 6 October 2023; Received in revised form 30 July 2024; Accepted 30 September 2024
Available online 15 October 2024
0921-8009/© 2024 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

activities, namely the trend of urbanization (and urban sprawl), industrialization, economic growth or high population pressure.

Following this line of thought, we set up a regional STIRPAT (STochastic Impacts by Regression on Population, Affluence and Technology) model to better understand the impact of region-specific population pressure, affluence or urbanization on local pollution and land transformation in Germany and to identify policy measures that could address both aspects at a time.

For this purpose, the remainder of the paper is organized as follows. Section 2 briefly discusses the role of urbanization for sustainable development, illustrates potential sustainability indicators at regional scale and reviews the empirical findings of region-based STIRPAT analysis in this context so far. Section 3 presents the STIRPAT model specification and describes the data. Sections 4 and 5 continue with the empirical application and the discussion of the results. Finally, the paper closes with concluding remarks and brief policy implications in Section 6.

2. Literature review

2.1. Sustainable development at urban level

Urbanization is a primary driver of biodiversity loss, carbon emissions, air pollution and changing land-use pattern (Rees and Wackernagel, 2008; Seto et al., 2012). Cities source about three-quarter of global GHG emissions (IPCC, 2014). According to Moran et al. (2018), urban areas host 60 % of the world population and produce 68 % of the global carbon footprint, and the 100 biggest cities emit 18 % of global GHG emissions. Air pollution is, to a large extent, a regional development question—the same holds for many environmental and sustainability topics. Ahlfeldt and Pietrostefani (2019) found a causal effect of higher density on pollution in OECD countries. They argue the effect of concentration in space overcomes the effect of reduced aggregate emissions. Urban areas concentrate people, human activity, and population in limited geographic regions. It leads to exceeding environment carrying capacity and increases the likelihood of irreversible damage. For instance, Baabou et al. (2017) estimates that each Athenian has an ecological footprint of about five global hectares, i.e., the surface of nature necessary to support its lifestyle. This mismatch between human needs and environment capacity stresses development – competition for resources – and the environmental resource viability. In sum, the urban and regional levels are most relevant to study sustainability and development patterns because they allow to account for spatial heterogeneity and broader diversity of patterns.

Besides global assessments, inquiries on specific relations between urban development and the environment have been carried out. Urban forms and urban growth are intertwined, and the environment should play a role in or be affected by this relationship. Castells-Quintana et al. (2021) show that globally more difficult climatic conditions (heat and water scarcity) associate with more urbanization. The association reveals non-linearities regarding urban concentration, size, and spatial structure. As a result, deteriorating climate conditions attract people to urban areas that will tend to sprawl and fragment simultaneously.

Cities and regions are diverse. Peri and Robert-Nicoud (2021) gather evidence in the literature and draw stylized facts stressing that urban forms affect GHG emissions heterogeneously across the globe. Studying 50 Japanese cities, Makido et al. (2012) found that residential-related CO_2 emissions per capita are negatively correlated with low fragmentation and regular urban forms and positively with densest and monocentric forms. They argue a non-linear pattern, especially when considering the transport sector. Density contributes to reducing per capita CO_2 emissions, but there is a turning-point from which more density leads to more CO_2 emissions. Mono-centricity is an aggravating condition. Lee and Lee (2014) investigate a similar relation by applying structural equation modelling framework to the 125 largest urban areas in the US. They estimate doubling density in those places reduces households' CO_2 emissions by 48 % regarding travel and 35 % regarding residential energy consumption. The mediating effect of monocentricity/fragmented urban structure reveals moderate. Burgalassi and Luzzati (2015) found similar null results in Italy, revealing urban sprawl comes with more CO_2 emissions. In this context, several studies point to potential conflicts of densification and the loss of green spaces, which are not only essential for promoting successful climate change adaptation but also improve air quality, and enhance human well-being (e.g., Erlwein et al., 2023; Wang, 2021).

Next to GHG emissions, air pollution is of serious concern for health and economic activity. For instance, Chang et al. (2019) estimate it reduces work productivity, even in service sectors that are less physically intense. This effect could be long-standing. Historical data on British industrial development analyzed by Hanlon (2020) proved that coal-induced air pollution lessened city employment and the working population in the long run. In UK as well and since the second industrial revolution, Power et al. (2023) show that industrialization and urbanization is a significant cause of variation in toxicity and composition of air pollution. Cities growth improves overall population health but comes with air pollution as a countervailing force (Ebenstein et al., 2015; Hanlon and Tian, 2015). Thereby, Kumar et al. (2015) argue that road vehicles are one of the major sources of air pollution in cities (see next section).

Generally, environmental changes affect socio-economic outcomes. For example, Bolognesi (2015) compares megacities development and finds the degree of land artificialization exacerbates cities' water vulnerability while a high degree of economic development attenuates it. A major part of literature analyzes the drivers of land take and soil sealing with the help of case studies (Naumann et al., 2019). But there are few studies comparing cases over time (using panel data analysis and/or the settlement and transport area as proxy for soil sealing).[1] Reasons for increasing space requirement differ little around the globe and strongly relate to urban expansion, population growth and economic development (Bieling et al., 2013; Schweizer and Matlack, 2014; Behnisch et al., 2016).

The complex and heterogeneous relations between urban and regional development and environmental conditions motivate the study of sustainability at the regional level, where both causes and consequences of unsustainable trajectories come with acute topicality (Truffer and Coenen, 2012; Brelsford et al., 2017; Peri and Robert-Nicoud, 2021). To tackle the challenge, modelling urban development as a social-ecological process is being developed (Cooper and Dearing, 2019). New types of indicators emerge to ease future empirical investigation and current decision-making. For instance, the Doughnut economics approach is being downscaled to the city level (Fanning et al., 2020), and so is the planetary boundaries framework (Hoornweg et al., 2016). Composite metrics that include social concerns enable the necessary rethinking of what is well-being at the urban level (see for instance Floridi et al., 2011 or Le Roy and Ottaviani, 2022).

2.2. Region-based STIRPAT analysis of local emissions and soil sealing

Germany, like any other member State of the EU, is legally bound to reduce air pollution and meet tightened thresholds set by the National Emission Ceilings Directive (NEC Directive) for sulphur dioxide (SO_2), non-methane volatile organic compounds (NMVOCs), ammonia (NH_3) and nitrogen oxides (NO_x). While the 2020 and even 2030 targets have already been achieved for SO_2 and NMVOCs, additional efforts are necessary to meet national ceilings for NH_3 and NO_x.[2] While ammonia

[1] One of the few studies, namely Bimonte and Stabile (2019), uses the number of building permits issued by public authorities as proxy for soil sealing.

[2] Considering NO_x almost all EU member states must substantially reduce emissions to meet the 2030 target (EEA, 2020).

largely relates to farming activities, NO_x is mainly driven by transport-related emissions, which account for about 43 % of the total. Transport-related emissions weigh twice those of the second leading contributor, the energy sector with no more than 21 %.

However, the trend of urbanization has not only resulted in higher levels of air pollution but also came along with rapidly increasing space requirements. Despite several national laws and EU legislations that serve to protect the land (cf. FederalBuilding Code § 1a, Federal Spatial Planning Act § 2) or to slow down the trend of soil sealing (cf. FederalSoil Protection Act § 1, § 5, Federal Nature Conservation Act § 1, Soil Framework Directive § 1) the demand for settlement and transport area still accounts for more than 50 ha per day (Behnisch et al., 2016).

Therefore, research interest for potential driving factors of NO_x emissions and soil sealing to ultimately evaluate the effectiveness of regulative measures raises. Methodological tools are manifold and include, among others, bottom-up sector-based analysis (e.g., Selvakkumaran and Limmeechokchai, 2015), integrated assessment and optimization models (e.g., Wang et al., 2015) or econometric analysis (e.g., Montero et al., 2021).

Belonging to the group of the latter, STIRPAT analysis often compare international trends and make use of country-specific panel data to identify anthropogenic factors of environmental impacts. Findings generally confirm the crucial role of a growing population and increasing affluence that trigger local air pollution and greenhouse gases (e.g., Scholl et al. (1996) for OECD countries, Timilsina and Shrestha (2009) for Asian countries, Andrés and Padilla (2018) for the EU) and soil sealing (e.g., Lai and Lombardini (2016) for regional drivers of land take in Italian coastal regions, Colantoni et al. (2016) for Athens' metropolitan region, Skog and Steinnes (2016) for urban areas in Norway).

Apart from population and affluence most impact studies (on both air pollution and soil sealing) also control for urban density and economic structures. Since average national levels of urbanization could be misleading, regional or city-based data gets preferred to gain in accuracy (e.g., Kenworthy and Laube, 1999; Lankao et al., 2009; Lankao et al., 2009; Karathodorou et al., 2010; Liddle and Lung, 2010; Travisi et al., 2010; Xu and Lin, 2016; Ge et al., 2018; Lv et al., 2019; Montero et al., 2021).

Finally, the relationship of economic activities and environmental outcomes (like air pollutants or land take) are also analyzed by using the environmental Kuznets curve (EKC) in order to measure potential non-linear anthropogenic impacts on the environment. The EKC thesis states that environmental degradation increases to a certain level as per capita income rises, and then decreases with high levels of per capita income. The EKC was originally introduced by Grossman and Krueger (1991), to demonstrate the connection regarding sustainable development and ecological destruction has the nature of an inverted U. The increasing degradation of the environment by growth is the consequence of a scale effect, and a composition and technique effect drive the decreasing degradation of environment.

Leal and Marques (2022) mention that one common interpretation of the EKC is the division into two phases, i.e. the early stage and later stages of economic development. The early stages are characterized by a decreasing capacity of ecosystem regeneration due to an intensive use of resources and a low capacity to pay for environmental degradation (characteristics of a pre-industrial or industrial economy). In contrast to, the later stages are defined by mitigation of environmental degradation due to increasing clean technological possibilities or environmental awareness associated with a higher level of (private and public) income (characteristics of a post-industrial economy). Recent meta and systematic analysis of the literature reveals that the hypothesis confirmation depends on the resource under scrutiny and the modelling approach (e.g., Pata, 2018; Sarkodie and Strezov, 2019; Pata, 2021 or Leal and Marques, 2022). Sarkodie and Strezov (2019) notice that most of the literature use atmospheric indicators as dependent variable. Land use appears under-investigated, and if studied, the focus is on deforestation or the effect of agriculture. Finally, the time coverage and the level of development of the selected countries affect the value of the turning point, on average US$ 8910 according to Sarkodie and Strezov (2019).

More recently, the literature investigates the non-linear relationship between income and environmental degradation by considering more complex forms. For example, Allard et al. (2018) point out that the N-shaped (cubic) EKC suggests that the original EKC hypothesis will not hold in the long run. It states that the scale effect (early stage) overcomes the composition effect (later stage) in a final stage occurring on the long run. Fakher and Inglesi-Lotz (2022) test the N-shaped relationship from 1994 to 2019 for 13 OPEC countries between GDP and six environmental indicators, including ecological footprint, pressure on nature or environmental performance. The hypothesis is confirmed only for four indicators. Wang et al. (2024) expand the scope of analysis to 214 countries, confirming the N-shaped EKC. So, increased economic growth once again leads to growing environmental degradation. Torras and Boyce (1998) argue that this can be due to reduced possibilities to further improve the distribution of industries, to decreasing returns on technological changes or that rising per capita income in the high developed countries is associated with increasing power inequality. Therefore, and to account for spatial non-linearities, Wang et al. (2022) test the mediating role of urbanization. They found no supportive evidence. Nonetheless, as development is pushed by spatial dynamics (Fujita et al., 2001) and its environmental effects related to local carrying-capacities of the ecosystems (Arrow et al., 1995), there is a need to explore further spatial patterns of EKC.

As EKC relates to size and composition effects, recently it has been implemented within a STIRPAT framework which allows to neatly distinct population, wealth and technological effects. Ge et al. (2018) or Arshed et al. (2021) incorporate the EKC effect into STIRPAT applications by adding non-linear terms. Further, Wu et al. (2024) find a N-shaped curve instead of confirming the classic EKC theory by studying 30 Chinese provinces from 2005 to 2019 and Arshed et al. (2021) show a U-shaped impact of GDP on CO_2 emissions studying 80 countries between 1990 and 2017. Obviously, there is need for future studies exploring non-linearities between development and environmental indicators regarding different settings for time and regions.

3. Empirical design

3.1. Model specification

Ehrlich and Holdren (1971) propose a conceptual framework for calculating environmental impacts of human development. This IPAT approach presumes that environmental impacts (I) are the multiplicative product of population (P), affluence (A) and technology (T) (Commoner et al., 1971; Ehrlich and Holdren, 1971) and can be written as follows:

$$I = P \bullet A \bullet T \tag{1}$$

While clarity and simplicity certainly add to the popularity of the IPAT approach, the pure identity undermines hypothesis testing and causal interpretation (e.g., York et al., 2003). This is why Dietz and Rosa (1997) suggest to transfer the IPAT equation into the so-called STIRPAT model that explains STochastic Impacts on the environment by Regression on Population, Affluence and Technology and provides the framework for empirical analysis:

$$I_{i,t} = c_t \bullet P_{i,t}^{\alpha} \bullet A_{i,t}^{\beta} \bullet T_{i,t}^{\gamma} \bullet e_{i,t}, \tag{2}$$

where $I_{i,t}$ is the environmental impact of country i at time t, $P_{i,t}$ is population, $A_{i,t}$ is affluence, $T_{i,t}$ is technology, c_t is the constant and $e_{i,t}$ is the residual error term. α, β and γ are the economic outcome elasticities with respect to population, affluence or technology, respectively. Jorgenson and Clark (2010) show that the logarithmic form of the STIRPAT equation gives a tractable regression equation and dampens the skewed

Table 1
Summary statistics.

Variables	Units	Mean	Standard Deviation	Minimum	Maximum
NO_x	kilotons	5.13	4.69	0.33	39.66
Settlement and transport area	km^2	12,120.62	6937.27	1316	62,906
Population	thousand	198.53	223.88	34.14	3629.16
GDP p.c.	GDP(€)/capita	27,538.82	13,145.27	6822	182,301
Car ownership	Cars/capita	0.55	0.07	0.21	1.14
Number of Houses	number	45,627.12	29,934.33	6779	332,052
Manufacturing	% of GDP	34.13	11.08	5.29	79.09
Urban density	inhabitants/km^2	279.43	646.47	35.95	4072.58

distribution of the variables. So, the model is setup according to Eq. (3)

$$lnI_{i,t} = lnc_t + \alpha \bullet lnP_{i,t} + \beta \bullet lnA_{i,t} + \gamma \bullet lnT_{i,t} + lne_{i,t}, \quad (3)$$

where technology $(T_{i,t})$ is assumed to be part of the error term, a combination of log-linear factors (like car ownership, urban density and share of industrial manufacturing) and time-fixed effects.

Global and regional STIRPAT studies generally refer to this model setup and often include the level of urbanization as a potential driver of environmental disruption. Furthermore, they control for transport indicators, which have a particular impact on sustainability at regional level (e.g., Liddle, 2013). Following this line of thought, the proposed model identifies impacts of population, per capita income, car ownership, urban density as well as the share of industrial manufacturing on regional NO_x emissions and land transformation of German districts between 1990 and 2020.

3.2. Data description

For the empirical application, a balanced cross-regional panel dataset (1990–2020) of 367 German districts and autonomous cities is used (NUTS 3). Additionally, the full sample is divided into two subgroups depending on a districts' settlement structure. The classification is derived from the criteria defined by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (Federal Institute for Research on Building, Urban Affairs and Spatial Development, 2022). There are 229 *large cities and urban counties* (e.g., Dortmund or Munich) if the number of inhabitants per squared kilometers is larger than 150. Similarly, there are 138 *rural and very rural counties* if the number of inhabitants per squared kilometers is smaller than 150 (e.g., Harz or Miesbach). Table 1 summarizes definitions, means and standard deviations of the variables used in the study.

Regional emissions are given by total NO_x emissions (measured in kilotons) and stem from the German Environment Agency (Umweltbundesamt, 2021). Transport-related NO_x emissions are responsible for the major part (of the change) of total NO_x-emissions regarding the considered time period. Though generally declining over time, Schneider et al. (2018) emphasize that local concentrations of nitrogen oxides still exceed policy targets and can be associated with serious impacts on health (e.g., asthma, hypertension, diabetes mellitus) in both, rural districts and autonomous cities. The data are available for a five-year interval.

Land-take for human settlement and transport has constantly increased over time putting additional pressure on the environment. However, more recently, policy has successfully limited land transformation to about 50 ha per day. The target is even more ambitious and equals 30 ha per day until 20,230 and net zero until 2050 (Umweltbundesamt, 2021). The yearly data stem from the German Regional Statistics Office (Statistisches Landesamt Baden-Württemberg, 2021).

Official statistics generally identify an increasing GDP per capita (measured in €) for the observed time period with regional disparities (Statistisches Landesamt Baden-Württemberg, 2021). Population, which largely varies with the regions' size and urbanization level, is generally increasing in the cities but rather stagnating or even shrinking in rural districts (Statistisches Landesamt Baden-Württemberg, 2021).

The average rate of private car ownership in Germany (used as a proxy for individual motorized transport) has continuously increased from an already high starting level of slightly below 500 cars per 1000 inhabitants in 1990 to more than 550 cars per 1000 inhabitants in 2020 (+14 %) without any breaks in trends in sight. Though the national trend is certainly driven by a particular dynamic development in rural districts, where the average rate of motorization increased by more than 25 % (from 491 cars per 1000 inhabitants in 1990 to more than 618 in 2020), car ownership is – maybe more surprising and despite an intensive debate on climate and environmental protection – also increasing in most German cities. The share of cars with combustion engines is still over 90 % in 2023 for Germany. Combustion engines in the traffic sector are a main source of NO_x emissions. Thus, car ownership is expected to have significant an influence on air pollution. The data are taken from the Federal Motor Vehicle Office (Kraftfahrt-Bundesamt, 2023).

While the number of private cars is still increasing, average annual NO_x emissions per private car are declining over time. This is due primarily to a cut of technology-driven specific emissions (NO_x/km) by more than 60 % from 80 mg/km in 2012 to 28 mg/km in 2020 for new registered cars in Germany (Kraftfahrt-Bundesamt, 2023). This favorable development is attributable to the gradual renewal of the vehicle fleet and more stringent emission standards. In addition, we observe, at least on average, stagnating or even slightly declining annual mileage per car in recent years (from slightly above 14,200 km per car in 2013 to about 13,300 km/car in 2020; Kraftfahrt-Bundesamt, 2023). Both trends can be observed for rural and urban districts but are more pronounced for the latter.

The number of houses increases permanently and is about 19 million in 2020 (Statistisches Bundesamt, 2021). Obviously, the number of houses partly represents the amount of land take. Naumann et al. (2019) identifies the need of more housing as a key driver of soil sealing. So, the number of houses is seen as an important control variable for this part of the analysis.

With regard to the remaining structural variables, urban density is defined as inhabitants per km^2. Dovey and Pafka (2014) show that there are various ways of defining urban density. Here, the variable is supposed to reveal effects due to a concentrated public infrastructure such as the shortening of distances and a general increase of mobility. Thereby, average urban density (279 inhabitants per km^2) is much higher and develop faster for the cities compared to the other districts. However, dynamics vary strongly across all types of regions. Districts surrounding major cities, for example, show similar or even more dynamic trends (probably due to lower land prices, less congestion, better expansion possibilities) compared to the cities themselves. The data for the share of industrial manufacturing (34 % of GDP in 2020) are taken from the State Office for Statistics Baden-Württemberg (Statistisches Landesamt Baden-Württemberg, 2021).

Table 2
Panel Unit Root Test (Hadri-LM-test).

Hadri-LM-test (z-statistic) Order of differences: 0 *H_0: All panels are stationary*							
NO_x	Settlement and transport area	Population	GDP p.c.	Car ownership	Manu-facturing	Number of Houses	Urban density
−0.81	105.77***	126.19***	74.20***	104.91***	66.28***	99.28***	126.19***

*** $p < 0.01$; Hadri-LM-test: Hadri-Lagrange-Multiplier-test; all variables are logarithmized; cross-sectional averages are substracted.

Table 3
Panel Unit Root Test (IPS Test).

IPS-test (*Z*-t-tilde-bar-statistic) Order of differences: 1 *H_0: Panels contain unit roots*							
NO_x	Settlement and transport area	Population	GDP p.c.	Car ownership	Number of Houses	Manu-facturing	Urban density
−47.10***	−23.94***	−22.24***	−28.03***	−26.44***	−26.42***	−29.15***	−22.24***

*** $p < 0.01$; IPS-test: Im-Pesaran-Shin-test assumes panel-specific AR parameters, Akaike Information Criterion is minimized; all variables are logarithmized; cross-sectional averages are substracted.

Table 4
Results of the Kao-, Pedroni- and Westerlund Cointegration Tests.

Kao-test *H_0: No cointegration*		**Pedroni-test** *H_0: No cointegration*		**Westerlund-test** *H_0: No cointegration*
NO_x, population, GDP per capita*, car ownership, manufacturing, urban density (all variables logged) / Soil Sealing, population, GDP* per capita*, number of houses, manufacturing, urban density (all variables logged)*				
Modified Dickey-Fuller t	-53.77*** / 5.79***	Modified Phillips-Perron t	-67.63*** / 23.78***	Variance ratio
Dickey-Fuller t	-26.97*** / 3.52***	Phillips-Perron t	-39.68*** / -15.75***	−2.88*** / 6.58***
Augmented Dickey-Fuller t	-16.76*** / -0.12	Augmented Dickey-Fuller t	-37.39*** / -11.89***	

*** $p < 0.01$; Kao-test assumes a constant cointegration vector; Pedroni- and Westerlund tests assume panel-specific AR parameters; cross-sectional averages are substracted.

4. Results

4.1. Preliminary tests

In order to take cross-sectional dependence (CSD) of variables into account, we conduct the preliminary tests with cross-sectional means subtracted variables and test procedures accommodating CSD.[3] Model application starts with unit root tests to determine the (non-) stationarity of variables. Therefore, the Hadri Lagrange Multiplier (LM) (with the null hypothesis that panels are stationary) and the Im-Pesaran-Shin (IPS) test (with the null hypothesis that panels are *not* stationary) is applied.

Both tests are based on the following equation (see Kao, 1999; Pedroni, 1999 or StataCorp, 2017):

$$lny_{i,t} = \rho_i \bullet lny_{i,t-1} + \gamma_i \bullet lnz'_{i,t} + lne_{i,t}, \quad (4)$$

where $y_{i,t}$ is the variable being tested and $z_{i,t}$ can represent panel-specific means, panel-specific means and a time trend or nothing. In general, panel unit-root tests are used to test the null hypothesis $H_0 : \rho_i = 1$ for all i versus the alternative $H_\alpha : \rho_i < 1$. So, unit root tests take the null hypothesis that the series contains a unit root, i.e. is not stationary. Only the Hadri LM test takes the null hypothesis that the series is stationary (versus the alternative that at least one panel contains a unit root).

It turns out that level variables (order of differences: 0) are not stationary for all variables (Table 2). Liddle (2011) points out that nonstationary variables change their mean, variance or covariance with other variables over time. Thus, OLS regressions with those variables in levels would be inefficient and most likely spurious. For example, t-statistics are no longer reliable.

In line with many STIRPAT literature, we therefore turn to the first-differences of variables. Indeed, first-differences are stationary (Table 3). So, the tests provide very strong evidence that all of the variables, as expected, are integrated of order 1 (I(1)) or nonstationary in levels but stationary in first differences.[4]

In addition, the variables are tested for panel cointegration. In case variables are not cointegrated, the long-term relationship is only weakly defined and the short-term relationship can be calculated by the estimation of a first-differences equation. If, however, variables are cointegrated, the estimation of first-differences would ignore a potential long-term relationship of the key variables and an error correction model should be applied to account for these dynamics (Engle and Granger, 1987; Liddle, 2011).

In order to check for cointegration, the Kao-, Pedroni- and Westerlund tests are applied.

All tests are based on the following panel data model (see Kao, 1999; Pedroni, 1999; Westerlund, 2005 or StataCorp, 2017):

$$lny_{i,t} = \beta_i \bullet lnx'_{i,t} + \gamma_i \bullet lnz'_{i,t} + lne_{i,t}, \quad (5)$$

where $y_{i,t}$ is a I(1) dependent variable and $x_{i,t}$ are the I(1) covariates. The vector $z_{i,t}$ allows to control for panel-specific effects and linear time trends. $\beta_{i,t}$ and $\gamma_{i,t}$ denote the cointegrating vector and a vector of coefficients, respectively. The null hypothesis of these tests states that $y_{i,t}$ and $x_{i,t}$ are not cointegrated by testing that $e_{i,t}$ is nonstationary. The alternative hypothesis states that the variables are cointegrated in all panels.

A clear majority of test statistics reject the null hypothesis assuming no cointegration (Table 4). Thus, there is strong evidence for a long-run

[3] Levin et al. (2002) suggest the subtraction of cross-sectional means to mitigate potential statistical impacts of CSD.

[4] Additionally, the Pesaran (2007) panel unit root test confirms that the series is integrated of order 1 (not shown). This test was explicitly developed for CSD variables.

cointegrating relationship among the respective variables, i.e., the evolution patterns of the variables are associated.

4.2. Regression results

Following the methodology outlined above, long-run impacts are estimated by using an error correction model. Therefore, the fully modified ordinary least squares (FMOLS) estimator is applied and long-run elasticities are estimated. The FMOLS estimator is applicable for cointegrated panel data and accounts for the heterogeneity that is present in the fixed effects as well as in the short-run dynamics. Further, the estimator addresses the cross-correlation between the cointegration equation error and the regressor innovations, mitigates potential remaining non-stationarity issues and provides consistent estimates in small samples. All in all, this estimator is very accurate in panels with heterogeneous serial correlation dynamics, fixed effects or endogenous regressors (Pedroni, 2001a; Pedroni, 2001b; Chakraborty and Ghosh, 2011).[5]

It is common to only use mean regressions as method, which might generate non-representative results for many of the counties included in the sample. Allard et al. (2018) argue that policy implications which are only based on results from mean regressions might therefore be ineffective. Therefore, the paper also calculates predicted margins for the two core variables of the STIRPAT model (i.e. population and GDP per capita). The margins are calculated from predictions of the previously fit model (i.e. FMOLS) at fixed values of the covariates (Williams, 2012). Basically, the idea of the margins is to see the marginal impact of a variable (like in a well specified OLS) but not on sample average. It focuses on "local" averages (i.e., percentiles, etc.).

Finally, the model is setup according to Eq. (3). As mentioned above, the term $T_{i,t}$ for technology is not estimated explicitly and is assumed to be part of control variables and time-fixed effects as well as the error term ($e_{i,t}$). Table 5 presents the results based on estimating Eq. (3) with NO_x emissions as dependent variable.

Table 5
Drivers of NO_x emissions.

Ln NO_x	(1) Full sample	(2) Large cities and urban counties	(3) Rural and very rural counties
Ln Population	0.94***	0.93***	1.11***
	(0.03)	(0.04)	(0.04)
Ln GDP p.c.	-0.01	0.04	−0.27***
	(0.08)	(0.10)	(0.08)
Ln Car ownership	0.41*	0.64**	0.64***
	(0.22)	(0.31)	(0.25)
Ln Manufacturing	0.17***	0.15*	0.31***
	(0.06)	(0.08)	(0.05)
Ln Urban density	-0.10 ***	-0.04	−0.37***
	(0.03)	(0.04)	(0.05)
Constant	-1.79**	−2.40**	1.65***
	(0.73)	(0.96)	(0.85)
R^2	0.57	0.65	0.64
Number of counties	367	229	138
Number of observations	2240	1384	855

***p < 0.01, **p < 0.05, *p < 0.1; Robust standard errors in parentheses; Year fixed-effects are included; Large cities and urban counties: inhabitants per km^2 > 150. Rural and very rural counties: inhabitants per km^2 < 150.

[5] Results based on standard estimators with CSD data may be biased and inconsistent. As Rahman et al. (2021) point out, FMOLS technique is appropriate to address CSD. There exist a range of studies using the FMOLS estimator in order to capture CSD dynamics (e.g. Dogan and Aslan, 2017 or Satrovic et al., 2021).

Table 6
Drivers of settlement and transport area.

Ln Settlement and transport area	(1) Full sample	(2) Large cities and urban counties	(3) Rural and very rural counties
Ln Population	0.59***	0.60***	0.14**
	(0.05)	(0.05)	(0.06)
Ln GDP p.c.	0.03	-0.02	0.05
	(0.29)	(0.03)	(0.04)
Ln Number of Houses	0.39***	0.38***	0.96***
	(0.05)	(0.05)	(0.06)
Ln Manufacturing	-0.05**	-0.04**	0.07***
	(0.02)	(0.02)	(0.02)
Ln Urban density	-0.39 ***	-0.33***	−0.60***
	(0.01)	(0.01)	(0.02)
Constant	-0.19	−0.01	0.05
	(0.31)	(0.28)	(0.40)
R^2	0.89	0.88	0.52
Number of counties	367	229	138
Number of observations	4367	2600	1766

***p < 0.01, **p < 0.05, *p < 0.1; Robust standard errors in parentheses; Year fixed-effects are included; Large cities and urban counties: inhabitants per km^2 > 150. Rural and very rural counties: inhabitants per km^2 < 150.

Column (1) shows the results for the full sample. Columns (2)–(3) show the results for urban (i.e. large cities and urban counties) and rural districts (i.e. rural and very rural counties) respectively. Population size positively and significantly effects NO_x emissions. This holds for the full sample as well as for the subgroups. For example, NO_x emissions rise by 0.94 % when population rises by 1 % (column (1)).

If controlled for car-ownership, the coefficient for GDP per capita is insignificant in two of three cases. Only in case of rural districts a significant negative impact can be observed (column (3)).

Private car ownership and the share of manufacturing both translate into higher NO_x emissions. This holds for all specifications.

With regard to urban density, coefficients indicate a significant and negative impact. While this holds for the full sample and the rural districts, the coefficient is insignificant for urban districts.

Table 6 presents the results based on estimating Eq. (3) with

Table 7
Drivers of NO_x emissions controlling for EKC.

Ln NO_x	(1) Full sample	(2) Large cities and urban counties	(3) Rural and very rural counties
Ln Population	0.96***	0.94***	1.14***
	(0.03)	(0.04)	(0.08)
Ln GDP p.c.	-3.64*	-4.00	3.71
	(1.93)	(2.73)	(4.51)
(Ln GDP p.c.)^2	0.18*	0.19	−0.20
	(0.09)	(0.13)	(0.22)
Ln Car ownership	0.28	0.52*	0.69
	(0.23)	(0.31)	(0.45)
Ln Manufacturing	0.19***	0.18***	0.31***
	(0.06)	(0.08)	(0.10)
Ln Urban density	-0.10 ***	-0.04	−0.41***
	(0.03)	(0.05)	(0.09)
Constant	16.72**	18.71**	18.42***
	(9.97)	(14.23)	(22.61)
R^2	0.01	0.03	0.01
Number of counties	367	229	138
Number of observations	2240	1384	855

***p < 0.01, **p < 0.05, *p < 0.1; Robust standard errors in parentheses; Year fixed-effects are included; Large cities and urban counties: inhabitants per km^2 > 150. Rural and very rural counties: inhabitants per km^2 < 150.

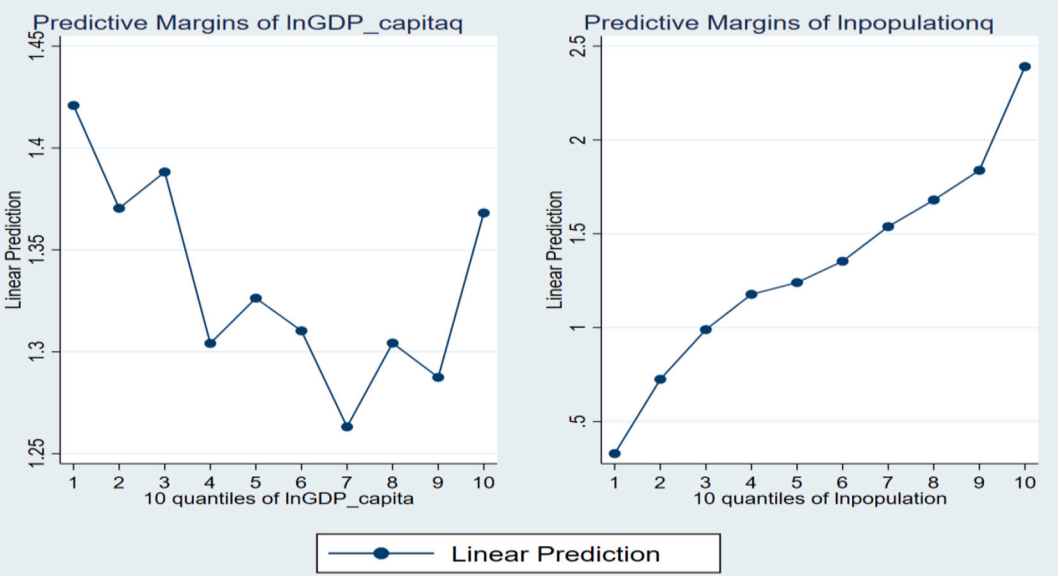


Fig. 1. Variation in GDP or population coefficient over the conditional percentiles regarding NO_x emissions.
***$p < 0.01$ for all coefficients; Number of observations: 2240.

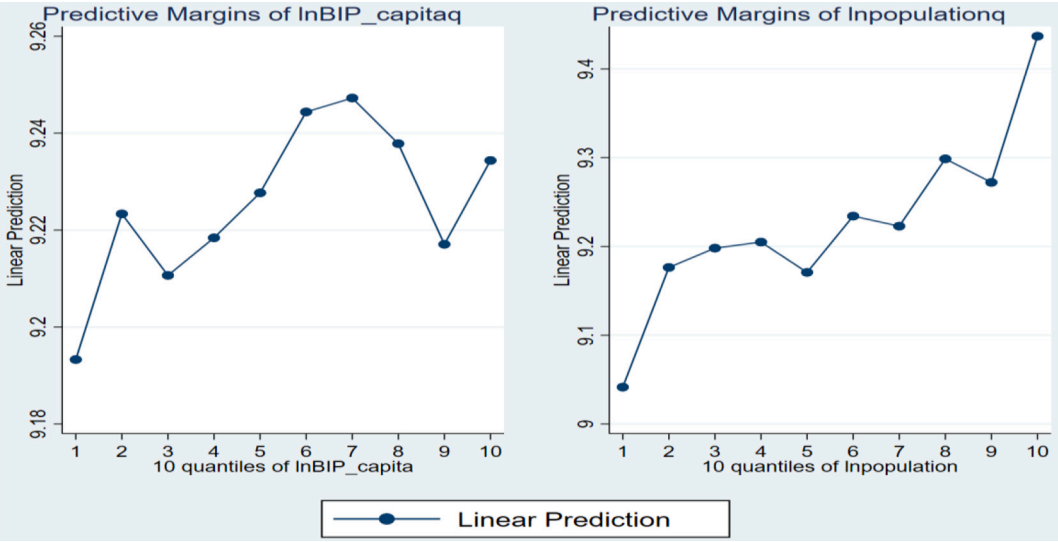


Fig. 2. Variation in GDP or population coefficient over the conditional percentiles regarding settlement and transport area.
***$p < 0.01$ for all coefficients; Number of observations: 4367.

settlement and transport area as dependent variable.[6]

Population size and the number of houses positively and significantly affects the settlement and transport area. This result holds for the full sample as well as for the subgroups.

The coefficient representing the impact of the share of manufacturing is negative for the full sample and the urban areas. In case of rural districts this coefficient shows a significant positive impact.

With regard to urban density, the respective coefficients indicate a significant and negative impact for both groups. However, the coefficient is double as high for rural districts.

Additionally, we check for potential non-linearities. First, a squared term for GDP per capita is included in Eq. (3) in order to control for potential EKC dynamics. Results show a U-shaped effect of GDP per capita on NO_x emissions in the case of the full sample (Table 7, column (1)). This kind of functional relationship is confirmed by for various estimation variations (not shown) but cannot be confirmed for the respective subgroups (EKC results regarding the settlement and transport area as well as investigating potential cubic relationships are only partly significant and not shown).

Second, Figs. 1 and 2 present the predicted margins of GDP per capita and population on NO_x emissions and settlement and transport area, respectively. Specifically, the predicted margins indicate how the predicted elasticities for GDP per capita or population succinctly differ across their percentiles. The predicted margins of GDP per capita are ranging non-monotonically for both dependent variables. In contrast to, the predicted margins of population increase with the respective percentile. For example, the effect of the 90th-percentile of population is almost 4 times higher compared to the 10th-percentile on NO_x emissions and is much more pronounced compared to the settlement and transport area.

[6] Note, that the model specification in Table 6 does not use car ownership as explaining variable. The reason is that the coefficient of car ownership (if included) is not significant and the goodness of fit decreases.

5. Discussion of results

In general, the results of this paper show that the development of local pollutants (NO_x emissions) and land take (settlement and transport area) is clearly related to population, GDP per capita, car ownership, number of houses, industrial manufacturing as well as urban density regarding German districts and autonomous cities in the long-run. In addition, findings show that the environmental impacts of variables partly depend on the underlying settlement structure (e.g., population density) or on the percentiles of the explaining variable. Specifically, results indicate that there exist differences regarding environmental impacts between *large cities and urban counties* and *rural and very rural counties*.

On the one side, car ownership, population and industrial manufacturing show positive effects on NO_x emissions independently of the regions' structure.

The findings confirm the important role of population with respect to environmental degradation for all estimation models. In line with existing studies analyzing other European regions (e.g. Lai and Lombardini, 2016 or Skog and Steinnes, 2016), this driving effect may be based on the level of energy consumption related to human activities. Further, findings indicate that the environmental impact of population increases with its respective percentile. So, high populated areas (not necessarily corresponding with high density) intensify emissions- and land-intensive activities. These complex dynamics are not found in other studies so far.

Moreover, positive impacts of motorization on environmental degradation can be found for both, rural and urban counties in case of NO_x emissions.[7] The rate of motorization reflects the share of individual motorized passenger transport, which is not only affected by the level of income but also by sheer necessities and persistent mobility patterns. Given the ongoing increase of motorization and the high share of cars with traditional combustion engines, which is particularly pronounced in rural counties but can also be observed for most of the cities, individual motorized transport will remain a clear driving force of local pollution in the near future. The increasing e-mobility could change the game in the medium- and long-run. Even with still increasing private car ownership, local emissions related to the internal combustion of fossil fuels may then lose in importance and other emissions (e.g., tyre abrasion, brake dust) might come to the fore. For the moment, however, electric cars still account for less than 25 % of new passenger car registration and much less considering private car fleet.

With regard to the structural factors, the findings show positive effects of industrial manufacturing on NO_x emissions and mixed results for settlement and transport area. Though declining over time, industrial production still adds significantly to local pollution. In addition, locations of industrial manufacturing are related to (heavy) freight transportation further contributing to higher NO_x emissions. In contrast to, industrial production only translates into higher settlement and transport area for rural areas. This result is in line with Debela et al. (2020) finding that large-scale industrial investments in peri-urban areas lead to substantial land use change. The negative coefficient regarding urban areas is perhaps due to efficiency synergies.

Additionally, results indicate a U-shaped effect of GDP per capita on NO_x emissions. This is in contrast to most of empirical studies following the EKC theory (see Section 2.2). Furthermore, there is some evidence of a N-shaped EKC. These results are not shown due to the weak robustness (i.e., there are only significant results for explaining NO_x emissions with GDP per capita and population alone). Probably, specific threshold levels of EKC dynamics are out of the sample range due to the relative high level of GDP per capita for German counties. The data do not build up the pre- and industrial phase of Germany, but the post-industrial phase with a focus on the tertiary sector. Leal and Marques (2022) states that "this third phase of economic development is characterized by a structural change in the economy, changing to information- and technology-intensive industries and a services-directed economy". The inconclusive results suggest that the EKC relationship should be studied with carefulness. Following Allard et al. (2018) the EKC dynamics depend on its underlying income structure. However, a large part of the existing literature on the EKC omit analyzing a potential cubic relationship in their estimations and thereby ignore the possibility of an N-shaped EKC (Allard et al., 2018).

On the other side, the results for GDP per capita and urban density depend on the considered regions. The findings show that the effect of GDP per capita is not significant in urban areas while being an important source of emission reduction in rural areas. Generally, people living in rural areas have not necessarily a higher level of education (although ongoing digitalization and increasing home-office opportunities may change this situation). But, people might have a deeper relationship with the existing natural environment and thus have higher preferences for environmental quality when living in rural areas. So, for example, larger amounts of higher income are spent for eco-friendly products and/or services. Moreover, the inclusion of car ownership potentially catches the emission-intensive part of affluence and thus reveals mitigating effects of GDP per capita on air pollution. In particular, this holds for rural areas with high private car ownership and low public infrastructure standards.

Further, findings confirm the negative correlation of urban density and environmental degradation found in most empirical studies in this field. It is likely that more densely populated regions allow for more competitive public transportation and (due to shorter distances) for more non-motorized individual transport. However, there is also a difference regarding a counties' settlement structure. Thus, a negative environmental impact of urban density can be shown for rural but not for urban counties in case of NO_x emissions. Probably, the mitigating effects of urban density on local pollutants are limited after passing a certain threshold. For example, Liu et al. (2022) show that different stages of urbanization have divergent impacts on air pollution.

Admittedly, the analysis misses, largely due to a lack of data at county level, explaining variables reflecting local weather conditions (could be an important criterion for the analysis of NO_x emissions) or public transport services. While public transport structures and related activities might partly be captured by urban density (even though the quality of services certainly differs among regions with similar density), weather conditions remain fully unconsidered. Following van Pinxteren et al. (2020) This could be particularly problematic for wind conditions, which can have a strong impact on local emission concentrations. However, it might be negligible if local weather conditions are relatively stable over time.

6. Concluding remarks

The paper presents a region based STIRPAT analysis that investigates anthropogenic impacts on local air pollutants (NO_x emissions) and land take (settlement and transport area). Unlike most other regional studies, the analysis is not limited to selected cities but covers almost all German counties between 1990 and 2020. Overall, the robust estimations confirm the appropriateness of the STIRPAT approach for estimating environmental impacts with respect to a small-structured regional setting (i.e. NUTS 3).

The findings, which are, due to existing cointegration dynamics between variables, based on long-run estimation techniques largely confirm the findings of related empirical studies (e.g., on the role of population, urban density, sectoral composition) but also provide new evidence of major driving forces of environmental degradation in a regional perspective. In particular we find positive impacts of

[7] If the subsample *rural and very rural counties* is again separated into *rural counties* and *very rural counties*, it can be shown that motorization rate has clearly the highest impact for *rural counties* compared to all other subgroups. The results are not shown due to less observations.

population, private car ownership (only for NO_x emissions) and share of industrial manufacturing for all regions. In contrast, GDP per capita and urban density show negative impacts on environmental degradation mostly for rural counties. Furthermore, results reveal non-linear dynamics of population and GDP per capita on NO_x emissions. Results suggest an inverted U-shaped relationship between GDP per capita and environmental degradation. However, the results are not robust regarding a potential cubic relationship. This is an interesting topic for future research of other (and economically different developed) regions.

Though results should not be interpreted in a general way but with respect to the underlying regional sample, the analysis leads to the following conclusions.

With regard to policies fighting local air pollution, the results highlight the crucial role of private car ownership. Thus, policies should further strengthen integrated mobility concepts with high shares of intermodal transport, easily accessible car sharing services, etc. At the same time, mobility patterns can be very persistent and (due to socio-demographic or topographic conditions) highly dependent on private cars. Thus, uniform pricing policies or the call for better public services and more bikelanes could, depending on the regions' exogenous environment, fall short of the mark and should be complemented by fostering the transition to low-emission car technology.

Further, it can be concluded that heterogeneity of settlement structure is clearly relevant for environmental effects and associated health and social impacts. So, policymakers should be aware of the fact that the effectiveness of measures depends on the regions' structure. For example, the density of buildings (and people) should be increased in rural areas in order to exploit its mitigating effects on local pollutants and to limit land take. In contrast to, this cannot be fully recommended for urban areas.

Last but not least, (urban) policymakers should take care of the increasing predictive margins regarding the effect of population on air pollutants and land take. The effects of higher population numbers on the environment should be tried to mitigate with densification. How to balance population size and density for sustainable development is surely an important area of further investigation.

CRediT authorship contribution statement

Johannes Lohwasser: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Thomas Bolognesi:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis. **Axel Schaffer:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Ahlfeldt, G.M., Pietrostefani, E., 2019. The economic effects of density: a synthesis. J. Urban Econ. 111, 93–107.

Allard, A., Takman, J., Uddin, G.S., Ahmed, A., 2018. The N-shaped environmental Kuznets curve: an empirical evaluation using a panel quantile regression approach. Environ. Sci. Pollut. Res. 25, 5848–5861.

Andrés, L., Padilla, E., 2018. Driving factors of GHG emissions in the EU transport activity. Transp. Policy 61, 60–74.

Arrow, K., Bolin, B., Costanza, R., Dasgupta, P., Folke, C., Holling, C.S., Pimentel, D., 1995. Economic growth, carrying capacity, and the environment. Ecol. Econ. 15 (2), 91–95.

Arshed, N., Munir, M., Iqbal, M., 2021. Sustainability assessment using STIRPAT approach to environmental quality: an extended panel data analysis. Environ. Sci. Pollut. Res. 28 (14), 18163–18175.

Baabou, W., Grunewald, N., Ouellet-Plamondon, C., Gressot, M., Galli, A., 2017. The ecological footprint of Mediterranean cities: awareness creation and policy implications. Environ. Sci. Pol. 69, 94–104.

Behnisch, M., Poglitsch, H., Krüger, T., 2016. Soil sealing and the complex bundle of influential factors: Germany as a case study. Int. J. Geo-Inform. 5, 132.

Bieling, C., Plieninger, T., Schaich, H., 2013. Patterns and causes of land change: empirical results and conceptual considerations derived from a case study in the Swabian Alb, Germany. Land Use Policy 35, 192–203.

Bimonte, S., Stabile, A., 2019. The effect of growth and corruption on soil sealing in Italy: a regional environmental Kuznets curve analysis. Environ. Resour. Econ. 74, 1497–1518.

Bolognesi, T., 2015, May. The water vulnerability of metro and megacities: an investigation of structural determinants. Nat. Res. Forum 39 (2), 123–133.

Brelsford, C., Lobo, J., Hand, J., Bettencourt, L.M., 2017. Heterogeneity and scale of sustainable development in cities. Proc. Natl. Acad. Sci. 114 (34), 8963–8968.

Burgalassi, D., Luzzati, T., 2015. Urban spatial structure and environmental emissions: a survey of the literature and some empirical evidence for Italian NUTS 3 regions. Cities 49, 134–148.

Castells-Quintana, D., Krause, M., McDermott, T.K., 2021. The urbanising force of global warming: the role of climate change in the spatial distribution of population. J. Econ. Geogr. 21 (4), 531–556.

Chakraborty, I., Ghosh, S., 2011. The relationship between financial development and economic growth and the Asian financial crisis: an FMOLS analysis. Int. J. Econom. Res. 2 (3), 88–101.

Chang, T.Y., Graff Zivin, J., Gross, T., Neidell, M., 2019. The effect of pollution on worker productivity: evidence from call center workers in China. Am. Econ. J. Appl. Econ. 11 (1), 151–172.

Colantoni, A., Grigoriadis, E., Sateriano, A., Venanzoni, G., Salvati, L., 2016. Cities as selective land predators? A lesson on urban growth, deregulated planning and sprawl containment. Sci. Total Environ. 545-546, 329–339.

Commoner, B., Corr, M., Stamler, P.J., 1971. The causes of pollution. Environ. Sci. Policy Sustain. Dev. 13 (3), 2–19.

Cooper, G.S., Dearing, J.A., 2019. Modelling future safe and just operating spaces in regional social-ecological systems. Sci. Total Environ. 651, 2105–2117.

Debela, D.D., Stellmacher, T., Azadi, H., Kelboro, G., Lebailly, P., Ghorbani, M., 2020. The impact of industrial investments on land use and smallholder farmers' livelihoods in Ethiopia. Land Use Policy 99, 105091.

Dietz, T., Rosa, E.A., 1997. Effects of population and affluence on CO2 emissions. Proc. Natl. Acad. Sci. 94 (1), 175–179.

Dogan, E., Aslan, A., 2017. Exploring the relationship among CO2 emissions, real GDP, energy consumption and tourism in the EU and candidate countries: evidence from panel models robust to heterogeneity and cross-sectional dependence. Renew. Sust. Energ. Rev. 77, 239–245.

Dovey, K., Pafka, E., 2014. The urban density assemblage: modelling multiple measures. Urban Des. Int. 19 (1), 66–76.

Ebenstein, A., Fan, M., Greenstone, M., He, G., Yin, P., Zhou, M., 2015. Growth, pollution, and life expectancy: China from 1991-2012. Am. Econ. Rev. 105 (5), 226–231.

EEA, 2020. National Emission Reduction Commitments Directive Reporting Status 2020.

Ehrlich, P.R., Holdren, J.P., 1971. Impact of population growth. Science 171 (3977), 1212–1217.

Engle, R.F., Granger, C.W., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica 251–276.

Erlwein, S., Meister, J., Wamsler, C., Pauleit, S., 2023. Governance of densification and climate change adaptation: how can conflicting demands for housing and greening in cities be reconciled? Land Use Policy 128, 106593.

Fakher, H.A., Inglesi-Lotz, R., 2022. Revisiting environmental Kuznets curve: an investigation of renewable and non-renewable energy consumption role. Environ. Sci. Pollut. Res. 29 (58), 87583–87601.

Fanning, A.L., Krestyaninova, O., Raworth, K., Dwyer, J., Hagerman Miller, N., Eriksson, F., 2020. Creating City Portraits: A Methodological Guide from the Thriving Cities Initiative.

Federal Institute for Research on Building, Urban Affairs and Spatial Development, 2022. Laufende Raumbeobachtung – Raumabgrenzungen.

Floridi, M., Pagni, S., Falorni, S., Luzzati, T., 2011. An exercise in composite indicators construction: assessing the sustainability of Italian regions. Ecol. Econ. 70 (8), 1440–1447.

Fujita, M., Krugman, P.R., Venables, A., 2001. The Spatial Economy: Cities, Regions, and International Trade. MIT Press.

Ge, X., Zhou, Z., Zhou, Y., Ye, X., Liu, S., 2018. A spatial panel data analysis of economic growth, urbanization, and NOx emissions in China. Int. J. Environ. Res. Public Health 15 (4), 725.

Grossman, G.M., Krueger, A.B., 1991. Environmental Impacts of a North American Free Trade Agreement.

Hanlon, W.W., 2020. Coal smoke, city growth, and the costs of the industrial revolution. Econ. J. 130 (626), 462–488.

Hanlon, W.W., Tian, Y., 2015. Killer cities: past and present. Am. Econ. Rev. 105 (5), 570–575.

Hoornweg, D., Hosseini, M., Kennedy, C., Behdadi, A., 2016. An urban approach to planetary boundaries. Ambio 45 (5), 567–580.

IPCC, 2014. Fifth Assessment Report. Cambridge Univ. Press.

Jorgenson, A.K., Clark, B., 2010. Assessing the temporal stability of the population/environment relationship in comparative perspective: a cross-national panel study of carbon dioxide emissions, 1960–2005. Popul. Environ. 32 (1), 27–41.
Kao, C., 1999. Spurious regression and residual-based tests for cointegration in panel data. J. Econ. 90 (1), 1–44.
Karathodorou, N., Graham, D.J., Noland, R.B., 2010. Estimating the effect of urban density on fuel demand. Energy Econ. 32 (1), 86–92.
Kenworthy, J.R., Laube, F.B., 1999. Patterns of automobile dependence in cities: an international overview of key physical and economic dimensions with some implications for urban policy. Transp. Res. A Policy Pract. 33 (7–8), 691–723.
Kraftfahrt-Bundesamt, 2023. Inländerfahrleistung 2013 und 2020, Bestand an Kraftfahrzeugen und Kraftfahrzeuganhängern nach Zulassungsbezirken 1990–2020, Durchschnittliche NO_x-Emissionen neu zugelassener Personenkraftwagen in Deutschland von 2012 bis 2020. Datenlizenz by-2-0.
Kumar, P., Khare, M., Harrison, R.M., Bloss, W.J., Lewis, A., Coe, H., Morawska, L., 2015. New directions: air pollution challenges for developing megacities like Delhi. Atmos. Environ. 122, 657–661.
Lai, S., Lombardini, G., 2016. Regional drivers of land take: a comparative analysis in two Italian regions. Land Use Policy 56, 262–273.
Lankao, P.R., Tribbia, J.L., Nychka, D., 2009. Testing theories to explore the drivers of cities' atmospheric emissions. Ambio 236–244.
Le Roy, A., Ottaviani, F., 2022. The sustainable well-being of urban and rural areas. Reg. Stud. 56 (4), 668–682.
Leal, P.H., Marques, A.C., 2022. The evolution of the environmental Kuznets curve hypothesis assessment: a literature review under a critical analysis perspective. Heliyon 8 (11), e11521.
Lee, S., Lee, B., 2014. The influence of urban form on GHG emissions in the US household sector. Energy Policy 68, 534–549.
Levin, A., Lin, C.F., Chu, C.S.J., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. J. Econ. 108 (1), 1–24.
Liddle, B., 2011. Consumption-driven environmental impact and age structure change in OECD countries: a cointegration-STIRPAT analysis. Demogr. Res. 24, 749–770.
Liddle, B., 2013. Urban density and climate change: a STIRPAT analysis using city-level data. J. Transp. Geogr. 28, 22–29.
Liddle, B., Lung, S., 2010. Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. Popul. Environ. 31 (5), 317–343.
Liu, H., Cui, W., Zhang, M., 2022. Exploring the causal relationship between urbanization and air pollution: evidence from China. Sustain. Cities Soc. 80, 103783.
Lv, Q., Liu, H., Yang, D., Liu, H., 2019. Effects of urbanization on freight transport carbon emissions in China: common characteristics and regional disparity. J. Clean. Prod. 211, 481–489.
Makido, Y., Dhakal, S., Yamagata, Y., 2012. Relationship between urban form and CO2 emissions: evidence from fifty Japanese cities. Urban Clim. 2, 55–67.
Montero, J.M., Fernández-Avilés, G., Laureti, T., 2021. A local spatial STIRPAT model for outdoor NOx concentrations in the community of Madrid, Spain. Mathematics 9 (6), 677.
Moran, D., Kanemoto, K., Jiborn, M., Wood, R., Többen, J., Seto, K.C., 2018. Carbon footprints of 13 000 cities. Environ. Res. Lett. 13 (6), 064041.
Naumann, S., Frelih-Larsen, A., Prokop, G., Ittner, S., Reed, M., Mills, J., Miturski, T., 2019. Land take and soil sealing—drivers, trends and policy (legal) instruments: insights from European cities. Int. Yearbook Soil Law Policy 2018, 83–112.
Pata, U.K., 2018. Renewable energy consumption, urbanization, financial development, income and CO2 emissions in Turkey: testing EKC hypothesis with structural breaks. J. Clean. Prod. 187, 770–779.
Pata, U.K., 2021. Renewable and non-renewable energy consumption, economic complexity, CO 2 emissions, and ecological footprint in the USA: testing the EKC hypothesis with a structural break. Environ. Sci. Pollut. Res. 28, 846–861.
Pedroni, P., 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxf. Bull. Econ. Stat. 61 (S1), 653–670.
Pedroni, P., 2001a. Fully modified OLS for heterogeneous cointegrated panels. In: Nonstationary Panels, Panel Cointegration, and Dynamic Panels. Emerald Group Publishing Limited.
Pedroni, P., 2001b. Purchasing power parity tests in cointegrated panels. Rev. Econ. Stat. 83 (4), 727–731.
Peri, G., Robert-Nicoud, F., 2021. On the economic geography of climate change. J. Econ. Geogr. 21 (4), 487–491.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econ. 22 (2), 265–312.
Power, A.L., Tennant, R.K., Stewart, A.G., Gosden, C., Worsley, A.T., Jones, R., Love, J., 2023. The evolution of atmospheric particulate matter in an urban landscape since the industrial revolution. Sci. Rep. 13 (1), 8964.
Rahman, M.M., Nepal, R., Alam, K., 2021. Impacts of human capital, exports, economic growth and energy consumption on CO2 emissions of a cross-sectionally dependent panel: evidence from the newly industrialized countries (NICs). Environ. Sci. Pol. 121, 24–36.
Rees, W., Wackernagel, M., 2008. Urban ecological footprints: Why cities cannot be sustainable—And why they are a key to sustainability. In: Urban Ecology. Springer, Boston, MA, pp. 537–555.
Richardson, K., Steffen, W., Lucht, W., Bendtsen, J., Cornell, S.E., Donges, J.F., Rockström, J., 2023. Earth beyond six of nine planetary boundaries. Sci. Adv. 9 (37), eadh2458.
Sarkodie, S.A., Strezov, V., 2019. A review on environmental Kuznets curve hypothesis using bibliometric and meta-analysis. Sci. Total Environ. 649, 128–145.
Satrovic, E., Ahmad, M., Muslija, A., 2021. Does democracy improve environmental quality of GCC region? Analysis robust to cross-section dependence and slope heterogeneity. Environ. Sci. Pollut. Res. 28, 62927–62942.
Schneider, A., Cyrys, J., Breitner, S., Kraus, U., Peters, A., Diegmann, V., Neunhäuserer, L., 2018. Quantifizierung von umweltbedingten Krankheitslasten aufgrund der Stickstoffdioxid-Exposition in Deutschland. Umweltbundesamt 1, 2018.
Scholl, L., Schipper, L., Kiang, N., 1996. CO2 emissions from passenger transport: a comparison of international trends from 1973 to 1992. Energy Policy 24 (1), 17–30.
Schweizer, P.E., Matlack, G.R., 2014. Factors driving land use change and forest distribution on the coastal plain of Mississippi, USA. Landsc. Urban Plan. 121, 55–64.
Selvakkumaran, S., Limmeechokchai, B., 2015. Low carbon society scenario analysis of transport sector of an emerging economy—the AIM/Enduse modelling approach. Energy Policy 81, 199–214.
Seto, K.C., Güneralp, B., Hutyra, L.R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proc. Natl. Acad. Sci. 109 (40), 16083–16088.
Shaw, S., Van Heyst, B., 2022. Nitrogen oxide (NOx) emissions as an indicator for sustainability. Environ. Sustain. Indicat. 15, 100188.
Skog, K.L., Steinnes, M., 2016. How do centrality, population growth and urban sprawl impact farmland conversion in Norway? Land Use Policy 59, 185–196.
StataCorp, 2017. Stata 15 Base Reference Manual. Stata Press, College Station, TX.
Statistisches Bundesamt, 2021. Kreisfreie Städte und Landkreise nach Fläche, Bevölkerung und Bevölkerungsdichte, Durchschnittliche NO_x-Emissionen neu zugelassener Personenkraftwagen in Deutschland von 2012 bis 2020.
Statistisches Landesamt Baden-Württemberg, 2021. Bruttoinlandsprodukt, Bruttowertschöpfung in den kreisfreien Städten und Landkreisen der Bundesrepublik Deutschland 1992 und 1994 bis 2019, Reihe 2, Kreisergebnisse Band 1, Hgg: Arbeitskreis "Volkswirtschaftliche Gesamtrechnungen der Länder" im Auftrag der Statistischen Ämter der 16 Bundesländer, des Statistischen Bundesamtes und des Bürgeramtes. Statistik und Wahlen, Frankfurt a. M.
Timilsina, G.R., Shrestha, A., 2009. Transport sector CO2 emissions growth in Asia: underlying factors and policy options. Energy Policy 37 (11), 4523–4539.
Torras, M., Boyce, J.K., 1998. Income, inequality, and pollution: a reassessment of the environmental Kuznets curve. Ecol. Econ. 25 (2), 147–160.
Travisi, C.M., Camagni, R., Nijkamp, P., 2010. Impacts of urban sprawl and commuting: a modelling study for Italy. J. Transp. Geogr. 18 (3), 382–392.
Truffer, B., Coenen, L., 2012. Environmental innovation and sustainability transitions in regional studies. Reg. Stud. 46 (1), 1–21.
Umweltbundesamt, 2021. NO_x-Emissionen nach Kreise 1990–2020.
van Pinxteren, D., Düsing, S., Wiedensohler, A., Herrmann, H., 2020. Meteorologische Einflüsse auf Stickstoffdioxid.
Wang, Z.-H., 2021. Compound environmental impact of urban mitigation strategies: co-benefits, trade-offs, and unintended consequence. Sustain. Cities Soc. 75, 103284.
Wang, H., Yin, W., Abdollahi, E., Lahdelma, R., Jiao, W., 2015. Modelling and optimization of CHP based district heating system with renewable energy production and energy storage. Appl. Energy 159, 401–421.
Wang, Q., Wang, X., Li, R., 2022. Does urbanization redefine the environmental Kuznets curve? An empirical analysis of 134 countries. Sustain. Cities Soc. 76, 103382.
Wang, Q., Li, Y., Li, R., 2024. Rethinking the environmental Kuznets curve hypothesis across 214 countries: the impacts of 12 economic, institutional, technological, resource, and social factors. Human. Soc. Sci. Commun. 11 (1), 1–19.
Westerlund, J., 2005. New simple tests for panel cointegration. Econ. Rev. 24 (3), 297–316.
Williams, R., 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. Stata J. 12 (2), 308–331.
Wu, C., Ge, M., Huang, Z., Wang, L., Liu, T., 2024. An extended STIRPAT model and forecast of carbon emission based on green consumption behaviors: evidence from China. Environ. Dev. Sustain. 26 (4), 8955–8977.
Xu, B., Lin, B., 2016. Regional differences of pollution emissions in China: contributing factors and mitigation strategies. J. Clean. Prod. 112, 1454–1463.
York, R., Rosa, E.A., Dietz, T., 2003. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecol. Econ. 46 (3), 351–365.