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RESEARCH ARTICLE

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Spatial patterns of built structures co-determine nations' level of resource demand

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Abstract

Societies' use of material resources is increasingly recognized as a key factor behind sustainability problems. The mass of materials used per capita and year differs substantially between countries. However, a limited range of variables (mostly per-capita gross domestic product [GDP]) were analyzed to explain this variation. Spatial patterns of cities influence their resource use, but the role of patterns of settlements and infrastructures as co-determinants of national-level material use is unknown, mainly due to lacking data to investigate their effects at that scale. Here we start closing this gap by systematically analyzing a broad set of potential determinants of national per-capita material demand, including built structures. Material demand is represented by both production- and consumption-based indicators. Among its potential determinants, we analyze eight novel indicators representing extent and spatial patterns of settlements and transport infrastructures in each country, along with GDP and other indicators considered so far. Analyzing 123 countries inhabited by 91% of the world population and accounting for 92% of world GDP, we show that built structures strongly co-determine resource use. Indicators of extent and spatial patterns of built structures have substantial additional explanatory power beyond GDP and other conventional indicators for both production- and consumption-based material flow indicators. The area of built-up land per capita emerges as the strongest predictor, but several other indicators representing built structures are also highly relevant. Limiting built-up land and designing spatial patterns of built structures hence deserve attention in attempts to reduce societies' resource throughput.

KEYWORDS
industrial ecology, infrastructure patterns, material footprint, material stocks, resource demand, settlement patterns

1 INTRODUCTION

Social metabolism—that is, societies' use of resources such as biomass, metals ores, fossil fuels, and non-metallic minerals—is linked with most sustainability issues (Haberl et al., 2019). The extraction of raw materials results in environmental problems ranging from ecological degradation and biodiversity loss due to intensive agriculture and forestry (IPBES, 2019) to environmental detriments and conflicts around mining (Luckeneder et al., 2021; Martinez-Alier, 2021), as well as concerns over depletion of non-renewable resources (UNEP, 2015). Wastes and emissions resulting from resource use drive global climate heating (IPCC, 2021), among many other problems. The global economy's circularity is low, and has deteriorated over the last century (Haas et al., 2020). Replacing fossil fuels with climate-friendly energy sources (e.g., photovoltaics and wind power) requires additional materials: not only small quantities of lithium, cobalt, vanadium, neodymium, etc. (Sovacool et al., 2020), but also large amounts of bulk materials such as concrete, steel, aluminum, and copper (Kalt et al., 2022). More sustainable resource use is therefore a pressing challenge (Ali et al., 2017). Reducing demand for material resources is, for example, recognized via policy targets in SDG 12.2 under the umbrella of "responsible consumption and production," and in SDG 8.4. under the umbrella of "decent work and economic growth."

The question emerges, which factors influence the resource demand of national economies. The national level is highly relevant because (1) nation states are important actors for resource policies and related fields such as energy, transport, and agriculture, and (2) most internationally comparable data are only available at the national level, as trade data for subnational units are generally lacking. As potential determinant of resource use, economic activity, as measured by gross domestic product (GDP) has attracted most attention: many studies have asked whether material use can be "absolutely decoupled" from "real" (inflation-corrected) GDP (Pothen & Welsch, 2019; UNEP, 2011). Posing the question like this implicitly assumes that resource use and GDP are strongly interlinked; that is, GDP (co)-determines resource use. A recent systematic review found 94 empirical studies (Wiedenhofer et al., 2020), all of which revealed strong, though not always perfect, linkages between resource use and GDP (Haberl et al., 2020). GDP can hence be expected to be a potent predictor of material demand, but as highly aggregated measure of the value of production and consumption it lacks details on many important social and economic issues. Other potential co-determinants have received less attention, which we address in this paper (see later).

Material demand of nations is assessed with two complementary approaches that apply different system boundaries to international trade: (1) The production-based approach of economy-wide material flow accounting includes all raw materials extracted on a nation's territory plus trade of products (including raw materials) flowing into or out of a country. Trade is accounted for as cross-border mass flow. This delivers the indicator "Domestic Material Consumption," abbreviated DMC (Fischer-Kowalski et al., 2011; Krausmann et al., 2017). (2) Consumption-based approaches combine data on raw material extraction with multi-regional input–output models to quantify how a nations final demand draws on raw materials extraction along global supply chains. This delivers an indicator called "Material Footprint," abbreviated as MF (also known as raw material consumption). This amounts to adding the material extraction required anywhere on earth to supply imported products (i.e., raw material equivalent of import), and subtracting the raw material equivalent of exported products (Eisenmenger et al., 2016; Lenzen et al., 2022; Wiedmann et al., 2015). In comparing countries with different sizes, most studies focus on per-capita values of extensive variables (e.g., material flows, energy use, and GDP).

While GDP is widely acknowledged as crucial co-determinant of resource use, few studies have analyzed GDP together with other factors. Factors co-determining national levels of per-capita DMC and MF have often been studied separately, and most studies covered only few potentially relevant determinants. Factors studied in addition to GDP include energy prices, climatic conditions, development status, and population density. Apart from GDP, the most widely studied factor is population density (number of inhabitants per km^2 of a country's territory) or its inverse, land area per inhabitant. A study of 15 EU countries in the year 2000 found an inverse correlation between population density and per-capita DMC (Weisz et al., 2006), as did an analysis of >100 countries worldwide that also included latitude as proxy for climate-related heating demand (Steinberger et al., 2010). In both cases, GDP played a much stronger role than population density; the latter mainly influenced biomass flows as well as ores and construction minerals. Climatic conditions only affected fossil-fuel demand, most likely due to heating requirements. The most encompassing study of possible determinants of DMC (Steger & Bleischwitz, 2011) used pooled time series data for the EU-15 from 1980/1992 to 2000 for a multivariate regression analysis that aimed at identifying the best-fit model drawing from >60 variables, which also included indicators for the availability of transportation networks. While stressing the importance of the energy and construction sector, their results suggest that population density influences DMC/capita/year as well as DMC/GDP, but with different signs: While population density was inversely correlated with DMC/cap/year, as in Steinberger et al. (2010), it was correlated with DMC/GDP. Later studies analyzing the material footprint per capita as well as DMC per capita found very little additional explanatory power of population density over exclusively GDP-based models (West & Schandl, 2018; Wiedmann et al., 2015). Many studies using multivariate statistical methods involved synthetic factors that are hard to interpret.

The role of spatial patterns of built structures (i.e., settlements and infrastructures) for the resource demand of cities is undisputed and well documented. Previous research has clearly established that the spatial layout of cities strongly affects their per-capita resource demand (Kenworthy, 2020; Newman, 1999; Seto et al., 2014). That the extent and spatial layout of settlements and infrastructures (henceforth denoted as "built structures") should also affect the level of resource throughput at the national scale is intuitively plausible: Establishment and maintenance of built structures requires large amounts of materials and energy. Settlement and infrastructure patterns are key factors determining how the economy can be supplied with physical goods and how personal mobility is organized, which subsequently co-determines energy requirements for mobility services (Prieto-Curiel et al., 2023). Floor space is related with energy use to heat or cool buildings, as well as with materials demand for construction (Creutzig et al., 2022; Hertwich, 2021; Krausmann et al., 2017; Sims et al., 2014). However, consideration of the role of built structures as potential co-determinants of national resource demand was so far not possible because it had been impossible to represent patterns of built structures at that scale through meaningful indicators: While maps of built structures (Haberl et al., 2021; Lanau & Liu, 2020; Schandl et al., 2020; Tanikawa et al., 2015) provide fine-grained spatial detail, they cannot be included in national-scale analyses without aggregation to the national level. This aggregation is challenging because it needs to preserve key information on spatial patterns, while reducing the information to national-level variables that enable analysis of cross-country patterns. Such indicators have recently become available and were used for an analysis of factors co-determining patterns of per-capita final energy use and CO_2 emissions (Haberl et al., 2023). We here apply these indicators to study the role of built structures as co-determinants of countries per-capita level of demand for material resources from a production- and consumption-based perspective, thereby also using an innovative statistical method ("lasso") allowing to identify the most important co-determinants among a large set of collinear independent variables.

The overarching goal of this paper is to advance the understanding of factors that co-determine national levels of per-capita material demand in both production- and consumption-based system boundaries. We do that by analyzing the dependence of resource use on (1) a set of "conventional factors" (GDP, population density, as well as indicators for energy prices, climatic conditions, the share of renewable energy [RENEW], and development status) and on (2) a set of indicators that describe aspects of settlement and infrastructures in each country that we suspect to be relevant in addition to conventional factors. DMC and MF of nations per capita were used as dependent variables, both of which are measured as tons of material flows per capita and year [t/cap/year]. In addition to nation's total material demand, we separately assess three major sub-categories into which DMC and MF are often partitioned, and whose patterns can differ considerably (Steinberger et al., 2010): (a) minerals and metals, (b) biomass, and (c) fossil energy carriers.

2 | METHODS AND DATA

2.1 | Indicators

This study is based on publicly available data and indicators (Table 1; Supporting Information S1). As dependent variables we use DMC per capita and year to represent the production-based perspective of a nation's material demand, and the MF per capita and year to represent the consumption-based perspective. Material flow data were taken from the UNEP-IRP database (UN-IRP, 2021).

We use two groups of independent variables (i.e., potential determinants) of DMC and MF, (1) "conventional factors"; that is, variables that have previously been considered in similar analyses based on data from official statistics, and (2) indicators representing extent and spatial layout of built structures at the national level in a consistent and harmonized manner (Haberl et al., 2023). In the following text, these are collectively denoted as "material stock patterns," in accordance with the socio-metabolic concept of societal "material stocks" (Haberl et al., 2019). The notion of "material stocks" is similar to concepts such as "in-use stocks" (Pauliuk & Müller, 2014), "technomass" (Inostroza, 2014), and "manufactured capital" (Weisz et al., 2015). Here we use eight indicators derived from that dataset, four describing important characteristics of built-up land and two each for roads and railroads (Table 1).

We use two variants of GDP, the standard version using market-exchange rates for currency conversions (GDP_{mexr}) and another variant based on purchasing power based conversions of currencies (GDP_{ppp}). While GDP_{mexr} is statistically more robust and better reflects the role of trade, GDP_{ppp} is more meaningful in terms of the volume of products and services created and consumed in each country per year. We also include population density [cap/km^2], abbreviated DENS. Climate-related heating requirements are included as heating-degree days (HDD) (Creutzig et al., 2015). The fraction of urban population related to total population of a country (UPOP) serves as development indicator (Krausmann et al., 2016), and the price of gasoline (PGAS) is included to reflect possible influences of energy prices on settlement patterns and fuel demand (Creutzig, 2014). We also include the share of RENEW sources in total energy use, as energy use from renewable sources provide an alternative to finite non-renewable resources such as fossil fuels. In order to facilitate comparisons of different-sized countries, we expressed all extensive variables as per-capita values. All data refer to the period 2015–2020; if data were available for several years in that period, we calculated arithmetic means of all available data points to reduce the effect of year-to-year fluctuations. Data on material stock patterns were only available for 1 year (2015 for built-up land, 2020 for transport infrastructures); for detail see the original source (Haberl et al., 2023). Data analysis is conducted in natural logarithms to linearize relationships.

Data were taken from the following sources: DMC and MF were taken from the UNEP-IRP material flow database (UNEP-IRP, 2022). GDP_{mexr} and GDP_{ppp} were taken from the UN Statistics Division National Accounts (UNSTATS, 2022) and World Bank databases (World Bank, 2022). The World Bank database was also used for DENS, UPOP, PGAS, and RENEW. HDD were taken from the International Energy Agency (IEA) Weather for Energy Tracker (IEA, 2022). All material stock pattern indicators were taken from Haberl et al. (2023); this study also reports on methods and data used to derive these indicators, as well as their correct interpretation. All data are provided online as Supporting Information S1.

TABLE 1 Variables and hypotheses analyzed in this study. For independent variables, we give a short justification for their inclusion and the hypothesized influence of the respective factor on per-capita material demand.

Acronym	Explanation
Dependent variables (material use)	
DMC	Domestic material consumption [kg/cap/year]. DMC is defined as mass of domestic extraction of raw materials plus import minus export; trade flows are counted as mass crossing the border. DMC measures the mass of all products used in a national economy (production-based perspective). In addition to aggregate DMC, we also analyze DMC_{bio} (biomass), DMC_{min} (minerals and metal ores), and DMC_{foss} (fossil fuels).
MF	Material footprint [kg/cap/year]. Mass of national extraction of raw materials plus raw material equivalent of imports minus raw material equivalent of exports. The MF represents the mass of extraction anywhere on earth related to the goods and services consumed by the population of a nation. In addition to the aggregate MF, we also analyze MF_{bio}, MF_{min}, and MF_{foss}.
Independent variables (potential co-determinants)	
(a) Conventional factors	
GDP_{mexr}	Gross domestic product per capita and year [$/cap/year], calculated using market-exchange rates and deflated to constant 2015 prices, assumed to be positively related with material demand.
GDP_{ppp}	Gross domestic product per capita and year [$/cap/year], calculated using purchasing power parities and deflated to constant 2017 prices, assumed to be positively related with material demand.
DENS	Population density [cap/m^2], population divided by the area of each country's territory. DENS is assumed to be inversely related with material demand due to lower resource availability in densely settled countries, and due to shorter transport distances.
HDD	Heating-degree days, an indicator of climate-related heating demand [°C × days (below 18°C)]. HDD are expected to raise material use due to fuels required to meet higher heating requirements.
UPOP	Urban population as fraction of a country's total population [%]. UPOP is an important development indicator and assumed to be positively correlated with material use, as the transition from agrarian to industrial society progresses.
PGAS	Price of gasoline [$/liter], an energy price indicator that has been shown to be strongly related with settlement patterns. PGAS is assumed to be inversely related with material use, as higher mobility costs should contribute to limiting sprawling low-density settlement patterns, and because higher fuel prices incentivize fuel sparing.
RENEW	Renewable energy consumption as the share of renewable energy in total final energy consumption [%]. RENEW is expected to have a negative effect on material use as renewable energy sources are substitutes of non-renewable resources.
(b) Material stock pattern indicators related to total built-up land	
BL_{cap}	Area of built-up land per capita [m^2/cap]; high BL_{cap} is expected to be related with larger resource use, because more resources are required to construct, maintain, and use larger settlements and infrastructures.
BL_{disp}	Dispersion of built-up land [dimensionless], measured by an index calculated based on the average distance of each patch of built-up land to the nearest adjacent patch. High values indicate strong dispersion and are thought to drive up resource demand due to longer infrastructure networks and more transport energy.
BL_{mono}	Monocentricity of built-up land [%], an index revealing to what extent a country is dominated by one large center. Defined as area of the largest contiguous built-up patch as per cent of the area of the 10 largest contiguous built-up patches of a country. High values indicate dominance of one large center and may result in lower demand for transport between many dispersed centers; although other effects are also conceivable.
UP_{dens}	Urban population density [cap/m^2]. Urban population per unit of urban built-up land. High UP_{dens} is thought to reduce urban material demand for transport infrastructures as well as energy demand for urban transportation.
(c) Material stock pattern indicators related to transport infrastructures	
RL_{cap}	Road length per capita [m/cap]; i.e., the total length of roads per capita of a country's population [m/cap]. RL_{cap} is assumed to be positively related with per-capita resource use due to resource requirements related to construction and use of roads.
RD_{urban}	Density of roads in urban areas [m/m^2]. RD_{urban} is assumed to be inversely related to material use due to the better connectivity of cities with a dense road network, which has proven to be important in many city-scale studies (Creutzig et al., 2015).
RWL_{cap}	Total railway length per capita of the entire population [m/cap]. Similar reasoning as with roads.
RWD_{total}	Total railway density per potential settlement area [m/m^2]. Potential settlement area is the "inhabitable" part of each country's territory. Higher railway density may have different effects: on the one hand it allows higher volumes of resource supply, on the other it might also reduce use of cars or lorries for transport, thereby reducing resource consumption.

2.2 | Statistical analyses

2.2.1 | Correlation and semi-partial correlations

The correlation coefficient is a standard statistical measure used to describe the strength of a linear relationship between two variables. It is bounded between −1 and 1. A correlation of 1 (−1) describes a perfect linear positive (negative) association or a direct (inverse) relationship between independent and dependent variable. A correlation coefficient of 0 means there is no linear relationship between the variables. The *squared correlation* is the r-squared of the linear regression of one of the two variables on the other, thus measuring the proportion of total variation explained by the predictor in the model.

Semi-partial (or part) correlations are used to analyze the additional explanatory power of variables over one specific predictor (in our case GDP_{ppp}). Consider Y as determined by $X = \{X_i, X_{-i}\}$. The semi-partial (or part) correlation between Y and X_i controlled for X_{-i} measures the correlation between Y and the part of X_i that is orthogonal to the other predictor X_{-i}. In simpler terms, a semi-partial correlation isolates the unique contribution of X_i to the relationship with Y, removing overlap or influence of other predictors.

The *squared* semi-partial correlation coefficient measures the change (either increase or decrease) in the model's r-squared value in the linear regression of Y on X when X_i is either added or removed from the set of predictors. Essentially, it represents the fraction of the variance in the dependent variable Y that can be uniquely explained by X_i.

2.2.2 | Multivariate lasso analyses

The "least absolute shrinkage and selection operator" (lasso) is a widely used technique for model selection and prediction. Its primary goal is to identify a parsimonious set of variables (i.e., the smallest set of variables required for a good model) from a potentially extensive list of potential covariates. It can be applied even if those covariates are correlated with each other (collinear). Lasso accomplishes this by penalizing complexity and striving to create the most parsimonious possible model, guided by a specified criterion (Hastie et al., 2015; Tibshirani, 1996).

To understand, how lasso works, consider a linear model specification

$$Y = B_0 + B_1 X_1 + \cdots + B_P X_P + \epsilon$$

In this equation, we usually standardize the variables to account for differences in their scales. Lasso aims to estimate the model coefficients B_0 to B_p by minimizing the following expression:

$$\frac{1}{2N}(y - XB)'(y - XB) + \lambda \sum_{j=1}^{P} |B_j|$$

This term can be understood as follows: The first part represents the squared prediction error minimized by the classical least squares (LS) method. The second term is the "penalty" term introduced by lasso to achieve a parsimonious model. It involves the sum of the absolute values of the coefficients ($|B_j|$), multiplied by a penalty factor λ. This penalty discourages the inclusion of unnecessary variables. If λ is set to zero, lasso produces results equivalent to standard LS estimates, resulting in a model with maximum complexity. As λ increases, fewer coefficients are allowed to be non-zero, leading to a simpler model.

Selecting the right value of λ is crucial, and cross-validation (CV) is a widely used method for this purpose. CV helps determining the optimal model by finding the λ that results in the minimum out-of-sample mean squared prediction error (MSPE). It works as follows:

1. The dataset is divided into K random folds, typically with $K = 10$.
2. For each fold, the model is trained using data from the remaining folds.
3. The model's performance is evaluated on the fold left out by computing the out-of-sample deviance.
4. The process is repeated for all folds, yielding K out-of-sample performance estimates.
5. The overall model performance is assessed by computing the MSPE, which aggregates the errors from all K validation sets.

An additional metric often reported is the out-of-sample r-squared (OSr^2), which replaces the squared prediction error of the standard (in-sample) r^2 formula by the squared prediction error across validation sets. Unlike r^2, the OSr^2 can become negative because the data used for model estimation differ from the data used for model assessment. For a more in-depth explanation of the lasso approach and various methods for selecting the optimal λ please see Hastie et al. (2015), different methods to identify the optimal λ are presented in Zou (2006).

TABLE 2 Pairwise correlations between independent and dependent variables in the dataset used in this analysis. The number of asterisks denotes the significance level, *** is $p < 0.01$; ** $p < 0.05$; *$p < 0.1$; no star, not significant.

	DMC	MF	DMC_{bio}	MF_{bio}	DMC_{foss}	MF_{foss}	DMC_{min}	MF_{min}
GDP_{ppp}	0.788***	0.895***	0.207**	0.721***	0.801***	0.919***	0.773***	0.885***
DENS	−0.223**	0.004	−0.409***	−0.097	0.032	0.038	−0.168*	0.067
UPOP	0.667***	0.725***	0.160*	0.616***	0.633***	0.748***	0.694***	0.697***
HDD	0.514***	0.479***	0.204**	0.355***	0.537***	0.510***	0.475***	0.483***
PGAS	0.103	0.156*	0.186**	0.247***	−0.033	0.073	0.057	0.186**
RENEW	−0.353***	−0.445***	0.248***	−0.200**	−0.541***	−0.536***	−0.413***	−0.423***
BL_{cap}	0.701***	0.672***	0.412***	0.606***	0.596***	0.671***	0.686***	0.662***
BL_{disp}	0.083	0.246***	−0.283***	0.127	0.209**	0.298***	0.148*	0.236***
BL_{mono}	−0.137	−0.179**	−0.076	−0.097	−0.241***	−0.233**	−0.169*	−0.202**
UP_{dens}	−0.443***	−0.418***	−0.279***	−0.360***	−0.393***	−0.422***	−0.452***	−0.429***
RL_{cap}	0.634***	0.531***	0.565***	0.553***	0.399***	0.489***	0.561***	0.493***
RD_{urban}	0.045	0.089	0.017	0.094	0.040	0.064	0.058	0.094
RWL_{cap}	0.489***	0.469***	0.276***	0.399***	0.442***	0.493***	0.496***	0.492***
RWD_{total}	0.382***	0.521***	−0.065	0.362***	0.501***	0.576***	0.448***	0.562***

3 | RESULTS

To understand the underlying patterns in the dataset, we start by testing pairwise and semi-partial correlations among all dependent and explanatory variables. Results for GDP_{ppp} are shown here, results for GDP_{mexr} are qualitatively similar, and are reported in Supporting Information S2. As expected, we find that GDP_{ppp} is strongly correlated with DMC and the MF. MF indicators, including its components (MF_{bio}, MF_{foss}, and MF_{min}), are more strongly correlated with GDP_{ppp} than DMC and its component; the weakest correlation is found for DMC_{bio}. DENS is negatively correlated with DMC, as expected, but not with the MF; significant correlations are found for DMC_{bio} and DMC_{min}, both of which are to be expected because in high-density countries, less area is available per capita for domestic resource extraction, which usually dominates the DMC for biomass and mineral resources. UPOP is strongly positively correlated with all resource indicators, with the weakest correlation found for DMC_{bio}. PGAS has a relatively weak effect, and tends to be correlated more strongly with footprint indicators than with DMC and its components. RENEW is negatively correlated with all indicators except for DMC_{bio}, most likely because bioenergy is an important RENEW source.

Some of the material stock pattern indicators are also strongly correlated with DMC and the MF. BL_{cap} is strongly correlated with all dependent variables, even with biomass-related indicators. More or less in line with the expected pattern—that is, higher resource requirements at high levels of dispersion, BL_{disp} is positively correlated with the MF, but surprisingly not with DMC. Component indicators show the expected pattern (at varying and sometimes low levels of significance), with the exception of DMC_{bio}, where a significant negative correlation prevails. As expected, monocentricity (BL_{mono}) is negatively correlated with resource use, but strongly significant correlations only exist for fossil-fuel consumption. Also, in line with the hypothesized pattern, UP_{dens} is strongly negatively correlated with all resource-use indicators, with strongest correlations found for fossil fuels and mineral resources. As expected, RL_{cap} is strongly positively correlated with all resource-use indicators, while—contrary to expectations—RD_{urban} does not seem to have any effect at all. For RWL_{cap} and RWD_{total} we find the expected correlations.

The semi-partial correlations controlling for GDP (Table 3) show the explanatory power of each individual variable in addition to the effect of GDP. Variables that co-vary with GDP will lose explanatory power, while those varying independent of GDP may assume stronger correlations. In this setting, DENS gains explanatory power, especially in the case of DMC but also the MF, the biomass component of DMC and MF, as well as DMC_{min}. As expected, per-capita resource flows are lower at higher DENS, and UPOP has little explanatory power over GDP, indicating a strong collinearity between both independent variables. HDD are uncorrelated with all indicators, with the exception of the expected positive correlation between HDD and DMC_{foss}, but the effect is weak. As in the bivariate analysis in Table 2, PGAS has little explanatory power, except for the expected negative correlation with DMC_{foss} and MF_{foss}, but even this correlation is weak. Interestingly, RENEW loses explanatory power for DMC and the MF in the semi-partial analysis, but its positive correlation with biomass use (DMC_{bio} and MF_{bio}) remains, as does its inverse correlation with fossil-fuel use (DMC_{foss} and MF_{foss}).

Some material stock pattern indicators have strong explanatory power even if GDP is controlled for. BL_{cap} is strongly positively correlated with DMC, DMC_{bio}, and DMC_{min}, but largely uncorrelated with the fossil-fuel component of resource use, as well as all the MF indicators. Dispersion (BL_{disp}) is not significantly correlated with any of the indicators, except for DMC_{bio} (strongly negative) and MF_{foss} (positive). UP_{dens} maintains its negative correlations with resource use, but many correlations are not significant or weak (DMC, DMC_{bio}, DMC_{min}). Road length (RL_{cap}) is strongly

TABLE 3 Semi-partial correlations controlling for GDPppp. Meaning of asterisks are explained in the caption of Table 2.

	DMC	MF	DMC_{bio}	MF_{bio}	DMC_{foss}	MF_{foss}	DMC_{min}	MF_{min}
DENS	−0.323***	−0.107***	−0.438***	−0.187***	−0.067	−0.075**	−0.266***	−0.042
UPOP	0.107*	0.072*	0.004	0.108*	0.041	0.080**	0.165***	0.042
HDD	0.087	−0.029	0.106	−0.060	0.106*	−0.008	0.050	−0.017
PGAS	−0.040	−0.006	0.151*	0.119*	−0.180***	−0.094***	−0.085	0.027
RENEW	−0.006	−0.056	0.379***	0.131**	−0.209***	−0.146***	−0.080	−0.037
BL_{cap}	0.210***	0.066	0.374***	0.144**	0.051	0.040	0.204***	0.061
BL_{disp}	−0.084	0.060	−0.334***	−0.025	0.041	0.107***	−0.015	0.051
BL_{mono}	0.067	0.052	−0.024	0.091	−0.037	0.003	0.030	0.026
UP_{dens}	−0.109**	−0.029	−0.209**	−0.049	−0.047	−0.022	−0.126**	−0.046
RL_{cap}	0.263***	0.078*	0.535***	0.210***	−0.019	0.014	0.187***	0.040
RD_{urban}	−0.050	−0.019	−0.009	0.008	−0.057	−0.047	−0.036	−0.012
RWL_{cap}	0.074	−0.018	0.195**	0.011	0.010	−0.005	0.092	0.016
RWD_{total}	−0.125**	−0.032	−0.242***	−0.099	0.016	0.019	−0.031	0.027

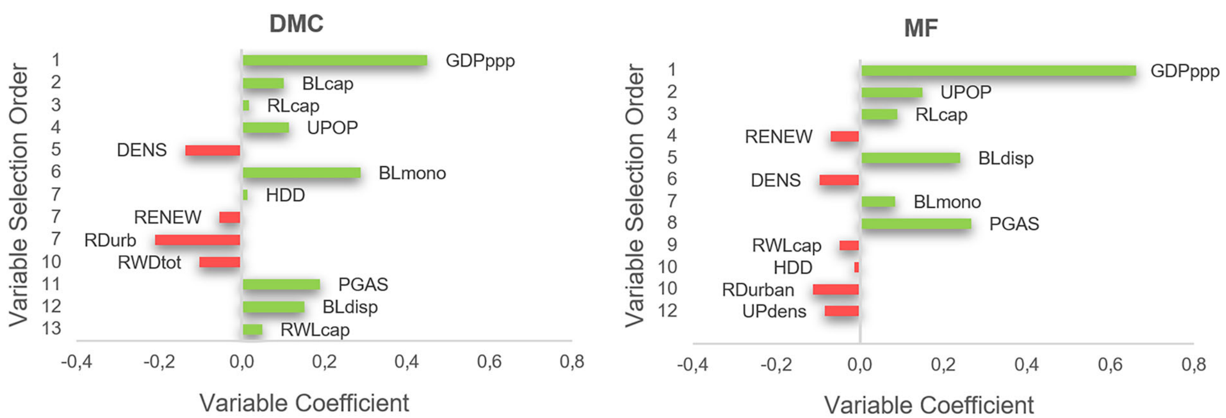

FIGURE 1 Graphical representation of the lasso analyses for all materials. Domestic material consumption (DMC) is shown in the left part, the material footprint (MF) in the right part. The lasso coefficients for each variable selected through cross validation is shown on the horizontal axis (negative values to the left, positive to the right). The relative order of selection in the lasso path is shown on the vertical axis. Indicators, including their acronyms, are explained in Table 1.

positively correlated with DMC, DMC_{bio}, MF_{bio}, and DMC_{min}, but only weakly with the MF and not with the others. Urban road density (RD_{urban}), and railway-related indicators have no or no strong additional explanatory power in the semi-partial analysis.

Pairwise and semi-partial correlations may be biased because the effect of excluded influential variables is ignored. To overcome this problem, we comprehensively assess the effect of all potential co-determinants using the lasso approach. Lasso identifies optimal models for predicting dependent variables based on a larger set of potential co-determinants, where co-determinants may also be collinear. The lasso approach adds (or removes, in the case of collinearity) determinants in a stepwise approach until the optimal model is established that balances the increasing predictive power of a larger number of predictors against the degrees of freedom rising with model complexity. The "lasso path" shows which variables are added or removed as λ is increased (i.e., complexity of the model is penalized more strongly). Variables selected early that remain active in the optimal model are particularly useful for predicting the independent variable. Because we aim to better understand the co-determinants of per-capita resource use and explore the role of built structures in this context, the core interest is, which independent variables are selected and how important material stock patterns are. Lasso shows this by revealing how early variables are selected, and how much additional explanatory power they have in the optimal lasso model.

Our lasso regressions for total DMC and MF using GDP at purchasing power parities (GDP_{ppp}) are shown in Table 4; results using GDP_{mexr} are reported in Tables S4–S7 in Supporting Information S2. Figure 1 presents a summary of the estimation results for the lasso model selected through cross-validation. In analyzing co-determinants of DMC, we find that GDP_{ppp} is selected as first independent variable, and BL_{cap} as second. Several other material stock pattern indicators contribute to the optimal model, and some are selected early on. In this case, the lasso analysis

TABLE 4 Results of lasso regressions for aggregated resource use (a) domestic material consumption (DMC) and (b) the material footprint (MF).

(a) Dependent variable: DMC

Lasso knots info					Lasso* estimation	
λ	Variable added or removed (R)	CVMSPE	OSr^2	r^2	Variable	CV lasso*
0.5075	GDP_{ppp}	0.4634	0.0714	0.1055	GDP_{ppp}	0.449
0.3498	BL_{cap}	0.3221	0.3546	0.3771	DENS	−0.137
0.2904	RL_{cap}	0.2778	0.4434	0.4685	UPOP	0.113
0.1662	UPOP	0.2013	0.5966	0.6193	HDD	0.014
0.1380	DENS	0.1894	0.6205	0.6443	PGAS	0.189
0.0597	BL_{mono}	0.1550	0.6895	0.7205	RENEW	−0.054
0.0311	HDD, RENEW, RD_{urban}	0.1491	0.7013	0.7463	BL_{cap}	0.102
0.0259	RWD_{total}	0.1490	0.7014	0.7519	BL_{disp}	0.151
0.0178	PGAS	0.1493	0.7009	0.761	BL_{mono}	0.287
0.0123	BL_{disp}	0.1489	0.7017	0.7678	RL_{cap}	0.017
0.0025	RWL_{cap}	0.1471	0.7053	0.7746	RD_{urb}	−0.211
*0.0008	(Unchanged)	0.1463	0.7068	0.7759	RWL_{cap}	0.049
0.0004	(Unchanged)	0.1467	0.706	0.7761	RWD_{tot}	−0.103
					Constant	−2.918

(b) Dependent variable: MF

Lasso knots info					Lasso* estimation	
λ	Variable added, or removed (R)	CVMSPE	OSr^2	r^2	Variable	CV lasso*
0.757	GDP_{ppp}	0.7845	0.090	0.136	GDP_{ppp}	0.662
0.171	UPOP	0.2141	0.752	0.767	DENS	−0.097
0.129	BL_{cap}	0.2018	0.766	0.784	UPOP	0.149
0.107	RL_{cap}	0.1966	0.772	0.792	HDD	−0.013
0.081	RENEW	0.1920	0.777	0.801	PGAS	0.266
0.074	BL_{disp}	0.1909	0.779	0.804	RENEW	−0.070
0.056	DENS	0.1876	0.782	0.812	BL_{disp}	0.240
0.039	BL_{mono}	0.1838	0.787	0.821	BL_{mono}	0.085
0.029	PGAS	0.1809	0.790	0.825	UP_{dens}	−0.084
0.022	RWL_{cap}	0.1797	0.791	0.831	RL_{cap}	0.089
0.020	HDD, RD_{urban}	0.1793	0.792	0.834	RD_{urban}	−0.113
0.017	UP_{dens}	0.1782	0.793	0.838	RWL_{cap}	−0.048
0.012	(R)BL_{cap}	0.1756	0.796	0.843	_cons	−3.186
*0.007	(Unchanged)	0.1732	0.799	0.846		
0.005	(Unchanged)	0.1740	0.798	0.847		

Notes: Lasso path provides information on the values of the penalty λ at which variables are added (or removed) from the model, arranged in decreasing order of λ (referred to as lasso knots). The penalty marked with an asterisk represents the λ value selected through cross-validation. Lasso* estimation (shadowed columns) displays coefficients estimated by the lasso model, incorporating the variables selected via cross-validation.
Abbreviations: CVMPSE, cross-validation minimum squared prediction error; OSr^2, out-of-sample r-squared, evaluated using the cross-validation folds; r^2, usual r-squared.

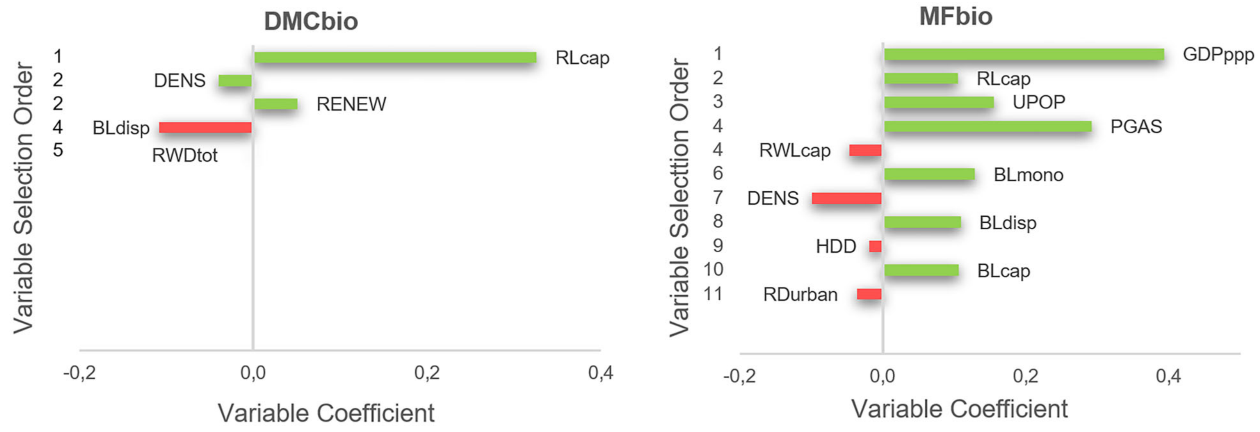

FIGURE 2 Graphical representation of the lasso analyses for biomass: left: DMC_{bio} and right: MF_{bio}. For explanation of the graph see caption of Figure 1. Details in Table S1 in Supporting Information S2. Indicators, including their acronyms, are explained in Table 1.

generated a complex model that includes many indicators, including most conventional factors and many of the material stock pattern indicators. The final model (two rightmost columns in Table 4) is capable of predicting the out-of-sample variation of DMC with an OSr^2 of 0.71. Most variables enter the model with the expected sign (RL_{cap}, RD_{urban}, RWD_{total}, BL_{disp}, and RWL_{cap}), while BL_{mono} shows a positive sign, which indicates that alternative explanations might be required to better understand this variable. Interestingly, PGAS and HDD enter with a positive sign, in contrast to the hypothesized relationships.

The model of the MF shown in Table 4b assumes an even higher overall explanatory power ($OSr^2 = 0.8$) than that of DMC. While UPOP is selected as second variable, after GDP_{ppp}, BL_{cap} is selected as third, but removed at the end of the lasso path due to collinearity with other variables. The final model includes several material stock pattern indicators, of which BL_{disp} has the largest coefficient; all material stock indicators have the expected sign, again with the exception of BL_{mono}. Conventional factors have the expected signs, except for PGAS (again with a positive coefficient) and HDD, which surprisingly has a negative coefficient.

In Figure 2 and Table S1 in Supporting Information S2, we analyze the drivers of biomass use; that is, the DMC_{bio} (Table 5a) and MF_{bio} (Table 5b). Interestingly, for DMC_{bio}, the best predictor model always selects indicators representing built structures, while GDP plays no important role. RL_{cap} enters as first variable, and has a high coefficient in the final model. The dispersion of settlements (BL_{disp}) enters early on, and assumes a negative coefficient, implying that countries with more dispersed settlements have lower DMC_{bio}. DENS is selected with the expected sign; that is, higher-density countries have lower DMC_{bio}, and RENEW raises DMC_{bio}, as can be expected because bioenergy is an important renewable fuel. The final model has only moderate OSr^2 of 0.29, implying that other factors may be more important for explaining DMC_{bio} than those present among our set of independent variables. Because DMC_{bio} strongly reflects national extraction of biomass, which in turn depends on factors favoring or hindering agricultural production and forestry, this suggests that explaining this resource-use indicator might need inclusion of factors characterizing endowment of countries with fertile land and the intensity of land use.

The model for MF_{bio} yields a much better prediction ($OSr^2 = 0.54$). In this case, GDP_{ppp} is selected as first variable, and several material stock pattern indicators are also included in the optimal model. The lasso path suggests that infrastructure-related indicators play an important role (RL_{cap} and RWL_{cap}); several conventional factors are also selected (UPOP, PGAS, DENS, and HDD). The positive sign and high coefficient for PGAS is a bit surprising. BL_{cap} enters late but with the expected sign and a relatively large coefficient in the final model.

Figure 3 reports on the lasso analysis for fossil fuels (details in Table S2 in Supporting Information S2). For DMC_{foss}, a simple, but effective ($OSr^2 = 0.67$) model can be forged with only five independent variables. GDP_{ppp} is selected first, RENEW second (and as expected with a negative sign), HDD as third variable (again with negative sign, as expected). BL_{cap} is selected as fourth variable, but with a high and positive coefficient. PGAS is the fifth variable, and as expected has a negative (but weak) effect.

The model of MF_{foss} includes more variables and has a very high OSr^2 of 0.86, implying that our set of independent variables includes most variables required for explaining cross-country patterns of MF_{foss}. GDP_{ppp} is again selected first, and with a very high positive coefficient, underlining the widely held conviction that fossil-fuel use and GDP of nations are strongly coupled. RENEW and UPOP come in second, respectively third, both with the expected sign. BL_{cap} band BL_{disp} are selected as fourth and fifth indicator, both with a positive coefficient, as expected. DENS also has the expected sign (negative) as does RD_{urban} (negative sign expected, as dense road networks reduce travel distances in cities). For both material use indicators, inclusion of the second/third variable (DENS and RENEW for DMC_{foss}, RL_{cap} for MF_{foss}) results in a substantially better model (higher OSr^2).

Figure 4 reports on the results related to nation's use of mineral resources (details in Table S3 in Supporting Information S2). In the model of DMC_{min} (Table 7a), GDP_{ppp} comes in as first variable, as expected with positive sign and a large coefficient (but lower than that for DMC_{foss}). BL_{cap}

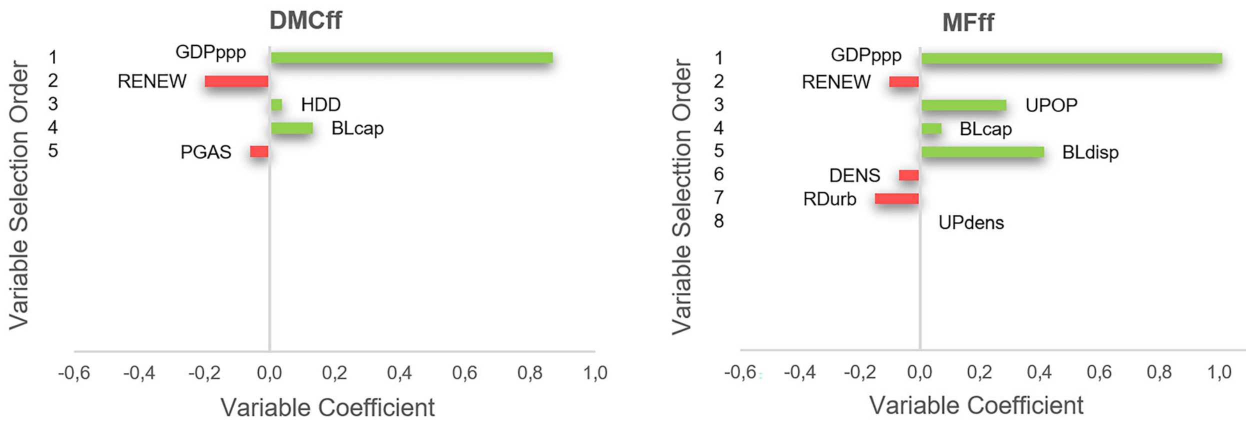

FIGURE 3 Graphical representation of the lasso analyses for fossil fuels: left: DMC_{foss} and right MF_{foss}. For explanation of the graph see caption of Figure 1. Details in Table S2 in Supporting Information S2. Indicators, including their acronyms, are explained in Table 1.

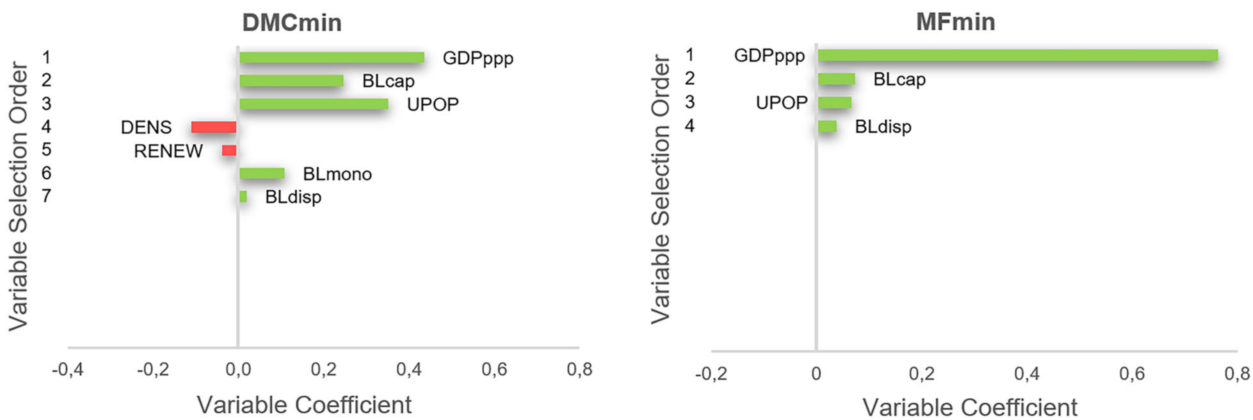

FIGURE 4 Graphical representation of the lasso analyses for mineral resources: left DMC_{min} and right MF_{min}. For explanation of the graph see caption of Figure 1. Details in Table S3 in Supporting Information S2. Indicators, including their acronyms, are explained in Table 1.

comes in second, and as expected has a large and positive coefficient. UPOP, DENS, and RENEW are also selected, with the expected signs. BL_{mono} and BL_{disp} are selected, but while BL_{disp} has the expected sign, we again find an unexpected positive coefficient for BL_{mono}. The overall model has a high OSr^2 of 0.65.

For MF_{min}, the model is even better ($OSr^2 = 0.76$) with fewer variables. GDP_{ppp} is again selected first, with an even higher positive coefficient than for DMC_{min}, but lower than for fossil fuels. The optimal model includes only four variables, two of them are material stock pattern indicators (BL_{cap} and BL_{disp}), both with the expected sign but relatively modest coefficients. UPOP is also selected, also with the expected positive sign and a low coefficient. For both DMC and the MF, it is noteworthy that the model based on GDP_{ppp} alone has a very low OSr^2, and the out-of-sample prediction jumps dramatically with inclusion of BL_{cap} as second variable.

4 | DISCUSSION

Our results support the widely held conviction that GDP plays a paramount role in co-determining countries' resource consumption (Charlier & Fizaine, 2023; Pothen & Welsch, 2019; Steinberger et al., 2010), and reveal that extent and patterns of built structures are important, so far overlooked co-determinants. GDP is the most influential determinant of both DMC and the MF, irrespectively of choice of GDP indicator (GDP_{ppp} or GDP_{mexr}; for the latter see Supporting Information S2, Tables S4–S7).

Regarding the components of material use, we confirm that GDP plays a large role for influencing fossil-fuel use; indeed, this relationship is strongest among all analyzed components of resource use. The correlation of GDP with use of mineral resources is also very strong, underlining the large role of construction activities for the monetary economy. Biomass use is least well-predicted by GDP: here both GDP indicators play a role for predicting the MF_{bio}, but not for explaining DMC_{bio}. This may be explained by the fact that DMC_{bio} is more strongly related with domestic extraction than with the material footprint (MF_{bio}) because upstream flows associated with traded biomass-based products are usually much larger than the mass of the traded product (Krausmann et al., 2008; Weisz et al., 2006; Wiedmann et al., 2015). While the MF_{bio} accounts for raw material extraction associated with traded products, and hence includes those large flows outside a country's borders, these flows are not represented by the DMC_{bio}. As GDP grows, countries often import more biomass-based products to raise their consumption of biomass-based products, which will affect their MF_{bio} but not their DMC_{bio}.

Our results clearly show that several factors co-determine nation's consumption of material resources, in addition to GDP—similarly to energy use and GHG emissions analyzed elsewhere (Haberl et al., 2023). Both conventional factors and indicators of built structures are important co-determinants, but their effects vary between the different system boundaries (DMC vs. MF) and components of resource use (biomass, fossil fuels, and mineral resources). For conventional factors, many of these correlations assume the hypothesized pattern outlined in Table 1; for example, we find the expected effects of population density (DENS) and the fraction of urban population (UPOP): DENS reduces resource use and UPOP is positively correlated. However, some of these factors play a small, and sometimes often difficult-to-interpret role. For example, PGAS plays a minor role for fossil fuels, and even acts counter-intuitively for biomass. The share of RENEW plays an important role, as expected: while renewables help in reducing fossil-fuel use, they are associated with higher use of biomass, most likely because bioenergy (fuel wood and biofuels) is the largest source of RENEW, currently providing 50%–60% of all RENEW worldwide (WBA, 2022).

Material stock pattern indicators are found to be highly important. In some of the regressions, they are among the most important co-determinants after GDP, and they are even more important than GDP for DMC_{bio}. Among the material stock pattern indicators, the area of built-up land per capita (BL_{cap}) emerges as the most influential indicator in many, but not all contexts. This is highly plausible: The larger the area covered with buildings and transport infrastructures, the more resources will be required to maintain and use buildings and infrastructures. Road surfaces, for example, need to be refurbished every 20–30 years, buildings are refurbished, and torn-down buildings are often replaced (Wiedenhofer et al., 2015). Moreover, buildings and roads require energy for being used, be it heating, cooling, or lighting energy for buildings or energy for vehicles on roads and railroads (Krausmann et al., 2020). The dispersion of buildings (BL_{disp}) and the length of transport infrastructures (e.g., RL_{cap} and RWL_{cap}) also mostly show the expected patterns. The results obtained using GDP at market-exchange rates instead of purchasing power parities (see Supporting Information S1) are overall rather similar. Again, BL_{cap} comes in as second-most important indicator for total resource use (DMC and MF) as well as mineral resources (DMC_{min} and MF_{min}) and fossil fuels. The only analysis where it drops out is that for DMC_{bio}.

Other results are more difficult to explain. Wherever BL_{mono} is selected, the sign of the correlation runs counter the initial hypothesis that a monocentric organization of built-up land would contribute to more efficient use of resources due to shorter transport distances. Instead, we find positive relations (i.e., more monocentric countries have higher resource throughput) in all analyses where BL_{mono} is selected as co-determinant. This finding could be a result of a co-variation of BL_{mono} with other variables not included in our analysis or result from historical contingencies. The consistency of these findings suggests that alternative explanations could be required; however, developing them would require additional analyses beyond the scope of this paper because this would most likely require inclusion of additional indicators and/or case-study work.

The dispersion indicator enters most analyses with the expected sign (higher resource use at higher dispersion), with the notable exception of biomass. One may hypothesize that the high land take of dispersed settlements might reduce nations capacity for domestic production of biomass, which would explain the strong effects on DMC_{bio} in both analyses (using GDP_{ppp} and GDP_{mexr}; see Supporting Information S2). In line with this hypothesis, BL_{disp} does not have an effect on MF_{bio} in the analysis using GDP_{ppp} and even a positive effect in the analysis using GDP_{mexr}, as reduced availability of fertile land could be counteracted by increased imports when countries assume higher affluence. Within the scope of the present work, however, this hypothesis cannot be corroborated.

Overall, our results support a number of interesting findings and policy-relevant insights. In summary, we find that including indicators of built structures prevailing in countries adds substantial explanatory value beyond GDP-based models of cross-country determinants of material use. Extent and spatial configuration of settlements and infrastructures emerge as highly important co-determinants of national economies' consumption of material resources, on top of the effect of economic activity and other factors considered so far in similar analyses. This result holds for both production-based and consumption-based indicators; that is, DMC and MF.

These findings imply that the role of spatial patterns of built structures, which has so far only been discussed for cities ("urban form"), but not for the entire continuum from highly dense urban centers to sub-urban and rural areas, must be considered at the national scale when aiming to explain cross-country differences in resource use (Weisz & Steinberger, 2010). Accordingly, the extent of built structures, and the spatial organization of society as reflected in material stock patterns, should receive more attention in social metabolism research and industrial ecology. The indicators we have proposed elsewhere (Haberl et al., 2023) and further analyzed in this paper hence open up new, highly relevant avenues for research into the determinants of nations' resource requirements beyond approaches that neglect the role of built structures.

Our results therefore are highly policy relevant, among others in the context of questions of sustainable production and consumption (SDG 12), as well as decent work and economic growth, specifically resource efficiency (SDG 8). Limiting growth of built-up land, and better designing spatial patterns of built structures, emerge as important levers for reducing the resource consumption of national economies. Insights from urban studies can provide guidance for better designing built structures beyond city limits, and achieve relevant improvements also at national scales.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The findings in this article are based on publicly available data. A compilation of the data used in the analysis is made available in Supporting Information S1.

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