Settlement and infrastructure patterns influence energy use and CO2 emissions almost as much as economic activity

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Abstract

Spatial patterns of settlements and transport infrastructures are known to influence per-capita energy use and CO2 emissions at the urban level1–4. At the national level, other potential determinants of energy use and CO2 emissions, primarily GDP, received much attention5–7, whereas the role of settlements and infrastructure patterns was disregarded due to lacking data. We present a set of novel national-level indicators derived from global satellite- and crowd-sourced maps to characterize extent and spatial patterns of settlements and infrastructures. We quantify these indicators for 113 countries and statistically analyze the results along with final energy use and territorial CO2 emissions, as well as factors usually considered in IPAT (impact = population x affluence x technology) approaches. We find that our indicators have similar explanatory power for energy use and CO2 emissions as GDP and IPAT factors. Covariates include built-up area, urban population density, the spatial clustering of built-up land, as well as transport networks, in addition to the effect of GDP. We conclude that the extent and spatial layout of settlements and infrastructures strongly affects resource use and emissions. Resource-sparing settlements and transport networks are under-appreciated options for reducing energy use and CO2 emissions.

Main

Rapidly progressing climate heating driven by growing greenhouse gas (GHG) emissions is a major concern[8]. GHGs mainly result from energy-related combustion of fossil fuels[9]. The question emerges, which factors drive energy use and emissions, and to what extent their trajectories can be altered. A widespread approach classifies drivers of emissions and resource use into population, affluence and technology[10–12]. These drivers are captured in the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) framework[10], derived from the classical IPAT (impact = population x affluence x technology) approach[12,13].

Economic activity (‘affluence’ in STIRPAT, usually measured as Gross Domestic Product or GDP) is acknowledged as a major driver of resource use and greenhouse gas (GHG) emissions[5–7]. The discussion mainly focuses on whether GDP can be ‘decoupled’ from emissions, i.e., whether energy use or emissions can be reduced while GDP is growing. This may be possible e.g. through more efficient technologies, but the debate is so far inconclusive[14,15]. While a recent study found that policies implemented in the last decade achieved reductions in CO_2 emissions in some growing economies[16], a meta-analysis yielded little evidence for reductions in energy use or GHG emissions consistent with ambitious climate targets in growing economies[17]. Other potential drivers received less attention than GDP. Population density has been studied with varied outcomes. Some studies found that low population density favors high per-capita resource use[18,19], other analyses found no[20] or opposite[21] effects. Relevant factors also include climatic conditions that drive energy demand for heating or cooling of buildings[22], fuel prices affecting demand for transport energy[23], and the urbanization rate (urban population as percent of total population).

At the urban scale, the influence of population density and the spatial layout of urban areas on cities' resource demand has been widely studied[1–4,22,24,25]. There are several reasons why the extent and spatial layout (density and form) of settlements and infrastructures – henceforth denoted as 'material stock patterns'[26], i.e. the spatial patterns of society's material stocks in infrastructures and buildings – should affect energy use and CO_2 emissions. The accumulation of material stocks requires massive amounts of resources such as steel-reinforced concrete, mortar, bricks, timber, plastics, glass, gravel, sand, etc.[27–30]. Heating, cooling or lighting of buildings and production processes in industrial plants require much energy[1,4,22,31], as does mobility of goods and people on roads and railways[30,32].

Despite these insights from urban studies, material stock patterns are largely ignored in debates on national-level decoupling[15,17] and STIRPAT analyses. We found only one STIRPAT study[33] considering material stock patterns in analyzing transport-related emissions. Hence little is known on the effects of material stock patterns on energy use and CO_2 emissions beyond the city level. This results from a scale mismatch: maps of material stock patterns provide fine-grained spatial detail[27] that cannot be interpreted at the national scale, where STIRPAT and decoupling research is conducted. For such analyses, spatial data need to be aggregated to the national level in a manner that preserves key information.

To address this research gap, we developed national-level indicators of material stock patterns focused on features of building and settlement patterns that, based on urban studies, might be potential determinants of resource use and emissions (Figure 1). We calculated the indicators presented in Table 1 for 113 countries comprising 91.2% of the world population and 97.3% of global GDP. Yearly total per-capita final energy use (abbreviated as TFC) was used as resource indicator, complemented by yearly per-capita CO_2 emissions (abbreviated as CO_2). To test material stock pattern indicators against other potential determinants of TFC and CO_2, we assembled a cross-country dataset of STIRPAT indicators including economic activity (GDP/cap/yr, abbreviated GDP), population density (DENS) and urban population as percent of total population (UPOP) as development indicator[34]. Heating-degree days (HDD) served as a proxy for climate dependency of energy demand[22] and the price of gasoline (PGAS) represented energy prices that are strongly related with settlement patterns[23]. Extensive variables were expressed as per-capita values to facilitate country comparisons and remove countries' population numbers from the analysis.

Results

National-level indicators of material stock patterns

We test three hypotheses based on aggregated indicators of material stock patterns (Figure 1), represented by three types indicators: (1) Built-up land is represented by two area indicators, one as fraction of a nation's inhabited land, the other area per inhabitant. Other indicators describe patterns of built-up areas, including their spatial clustering, form and distribution. (2) Road indicators that describe the density (length per unit

area) of roads in urban and rural regions and the relations between urban and rural road lengths and densities. (3) Railway indicators were defined in the same manner as those for roads (Table 1).

Table 1. Indicators of the extent and pattern of built-up land and transport infrastructures. These indicators condense spatially explicit information in maps to national-level indicator values assumed to co-determine a nation's per-capita level of energy use or CO_2 emissions. Global maps showing the indicator values are in Extended Data Figures 4-6.

Name	Abbreviation	Description and interpretation	Unit
(1) Indicators for the extent and pattern of a nation's built-up land			
Fraction of built-up land	BL_{fract}	Built-up land (buildings & infrastructures) as % of the inhabited land area.	m²/m²
Built-up land per capita	BL_{cap}	Built-up land per capita.	m²/cap
Dispersion of built-up land	BL_{disp}	Index based on the average distance of each patch of built-up land to the nearest adjacent patch. High values indicate strong dispersion.	–
Monocentricity of built-up land	BL_{mono}	Area of the largest contiguous built-up patch as % of the sum of the areas of the ten largest patches. High values indicate dominance of one large center.	m^2/m^2
Compactness of built-up land	BL_{comp}	Index describing how 'round' or 'compact' the shapes of a nation's built-up land patches are on average.	–
Urban population density	UPdens	Urban population per unit of urban built-up land	cap/m^2
(2) Indicators of road density and distribution			
Road density	RD_{total}	Length of roads per unit area of inhabited land.	m/m²
Urban road density	RD_{urban}	Length of roads in urban areas per unit area of urban areas.	m/m²
Rural road density	RD_{rural}	Length of roads in rural areas per unit area of rural areas; proxy of rural accessibility and connectivity between urban centers.	m/m²
Ratio of urban-to-rural road lengths	$RL_{urb\text{-}rur}$	Ratio of urban to rural road lengths, indicating the extent to which roads are concentrated in cities.	–
Ratio of urban-to-rural road density	$RD_{urb\text{-}rur}$	Ratio of RD_{urban} and RD_{rural}, indicating the difference between urban and rural road densities.	–
(3) Indicators of railway density and distribution			
Railway density	RWD_{total}	Length of railways per unit area of inhabited land.	m/m²
Urban railway density	RWD_{urban}	Length of railways in urban areas per unit area of urban areas.	m/m²
Rural railway density	RWD_{rural}	As RD_{rural} for railways.	m/m²
Ratio of urban-to-rural railway lengths	$RWL_{urb\text{-}rur}$	As $RL_{urb\text{-}rur}$ for railways.	–
Ratio of urban-to-rural railway	$RWD_{urb\text{-}rur}$	As $RD_{urb\text{-}rur}$ for railways.	–

density

Pairwise and semi-partial regressions

In terms of their Pearson correlation coefficients in pairwise regressions, several indicators of material stock patterns are as strongly correlated with TFC and CO_2 as common STIRPAT factors (Figure 2a). GDP is positively correlated with both TFC and CO_2. HDD and the fraction of urban population also show the expected pattern, while PGAS and DENS are largely uncorrelated. Almost all spatial indicators are correlated with both TFC and CO_2. The extent of built-up land (BL_{cap} and BL_{fract}) is positively correlated with both TFC and CO_2, as are total and rural road density and the dispersion of built-up land and most railway-related indicators. The correlation coefficients of BL_{cap} with TFC and CO_2 are both ~0.7; BL_{cap} is the second-best predictor of both TFC and CO_2 after GDP. As expected from the urban literature, urban population density (UP_{dens}) is inversely correlated with CO_2 and energy, whereas the share of urban population (UPOP) is a strongly positively correlated with CO_2 and TFC. Inverse relations prevail for BL_{mono}, BL_{comp} and the urban-to-rural relations of infrastructure density.

Semi-partial correlations of the material stock pattern indicators controlled for GDP and population density (DENS) are shown in Figure 2b. The part of each material stock pattern indicator correlated with GDP and DENS is removed, revealing the strength of the linear correlation between TFC or CO_2 and the remaining part of the respective variable. The distance from the vertical axis either to the right (positive correlation) or to the left (inverse correlation), depicts the additional explanatory power of the respective indicator over a model considering only GDP and DENS. Several indicators provide additional explanations over GDP and DENS alone. Built-up land (both BL_{cap} and BL_{fract}) is positively correlated with TFC and CO_2, as are the density of rail and road infrastructures, especially in rural areas. Like in urban studies, UPOP is inversely correlated with TFC and CO_2, as is urban road density (not significant) and BL_{mono}. PGAS, which had not been significant in the bivariate correlations, emerges as an important factor, which is also observed for RD_{urban} and other indicators. UP_{dens} loses importance, most likely due to its high correlation with GDP.

Multivariate models

The ability of the material stock pattern indicators to add insights beyond STIRPAT is further analyzed in Table 2, which summarizes an extended multivariate analysis, taking STIRPAT as reference. We performed stepwise regressions; variables were selected either only from STIRPAT indicators (rows labelled STIRPAT) or from all indicators (rows labelled ALL). Table 2 presents the statistically best parsimonious model in each category based on p values of an F-statistic in which models were tested with and without the respective variable in each step. Variables that were not significant in the semi-partial analysis (Fig 2b) were excluded. The final model is robust to the use of BIC as an inclusion/exclusion criterion. Hence, the best model was selected in terms of its ability to explain international differences in TFC or CO_2 with the least number of factors. In addition to analyses that included GDP as independent variable (part A of Table 2), we also

performed an analysis in which GDP was excluded (part B of Table 2). This analysis tested whether the cross-country patterns of TFC and CO_2 could be explained without resorting to economic activity as an explanatory variable. GDP is a global variable that is connected with many of the factors we analyze, thus this analysis reduces global multicollinearity problems and shows, which indicators have additional explanatory power in this multivariate setting. All variables are taken as logarithms; hence coefficients can be interpreted as elasticities, i.e. as the relative change in TFC, respectively CO_2, associated with a 1% change in the respective independent variable.

Table 2. Results of a stepwise multivariate regression analysis selecting the best parsimonious model in each category. A) including B) excluding GDP as explanatory variable. Rows STIRPAT show models constructed using only STIRPAT indicators, rows ALL show models where both STIRPAT and material stock pattern indicators were included as potential predictors. R^2max reports the R^2 of a model that includes all variables. Cells left empty indicate that the respective variable was not selected. The table includes the estimated OLS parameter, where *, **, *** indicates significance at 10, 5, 1%; red marks non-significant results.

	A) GDP included as explanatory variable				B) GDP excluded as explanatory variable			
	CO_2		TFC		CO_2		TFC	
	STIRPAT	ALL	STIRPAT	ALL	STIRPAT	ALL	STIRPAT	ALL
Intercept	-4.29***	-3.98***	2.73***	3.19***	-8.99***	-5.50***	-2.10***	0.76
GDP/cap	0.58***	0.44***	0.60***	0.55***				
DENS	0.02		-0.05*		0.07	-0.10	0.00	-0.06
UPOP	0.56***	0.46**	-0.05		1.86***	1.13***	1.29***	0.71***
HDD	0.11***	0.06***	0.05***	0.04***	0.16***	0.04	0.11***	
PGAS	-0.69***	-0.75***	-0.33***	-0.40***	-0.37**	-0.55***	0.00	-0.20*
BL_{cap}		0.27***		0.19***		0.34***		0.36***
RD_{urb}				-0.56***				
RD_{rur}						0.22***		
$RD_{urb-rur}$								-0.38***
RWD_{tot}		0.16***				0.93***		
RWD_{urb}								0.16***
RWD_{rur}						-0.69***		
BIC	190.82	168.23	104.12	67.50	256.15	205.50	221.83	159.69
AdjR^2	0.81	0.85	0.85	0.89	0.65	0.79	0.55	0.74
R^2	0.82	0.86	0.85	0.89	0.66	0.80	0.56	0.76
R^2MAX	0.88		0.92		0.83		0.81	

Models including material stock pattern indicators always have higher explanatory power than STIRPAT models, even in part A, where the STIRPAT models has strong explanatory power. If GDP is excluded, the STIRPAT model explains only 55% (adjusted R^2) of the variation for TFC and 65% for CO_2. By comparison, the best models in the ALL categories explain 74% of the variation for TFC and 79% for CO_2 when GDP is excluded (Table 2B). These latter models are almost as good as STIRPAT models that include GDP, which explain 85% of the variation for TFC and 81% for CO_2. BL_{cap} is always selected in ALL models, significant at the 1% level. DENS is not significant in any ALL model, and has little explanatory power in STIRPAT models. Other material stock pattern indicators are selected less frequently, but sometimes have high explanatory

power. Urban road density is strongly and inversely related with TFC, in line with urban findings that connectivity reduces transport energy[22]. In models excluding GDP (Table 2B), RD_{rur} and RWD_{total} are strongly positively related with CO_2, whereas RWD_{rural} is inversely related with CO_2, all of which are expected patterns. In the TFC model, the effect of $RD_{urb\text{-}rur}$ can be explained by the positive effect of a high urban road density, while we lack a straightforward explanation for the modestly positive relation between TFC and RWD_{urban}.

Discussion

The analysis confirms that the extent and spatial patterns of buildings and infrastructures play an important role in co-determining the level of resource use, here TFC and CO_2, hence insights from urban studies[1–4] hold at the national scale. Despite the unavoidable loss of information resulting from aggregation of maps to national-scale indicators, they still represent important characteristics of material stock patterns that strongly affect cross-country patterns of resource use and emissions. The indicators have additional explanatory power over STIRPAT approaches and allow building multivariate 'physical economy' models that explain international patterns of energy use and emissions well, even if GDP is excluded. Altogether, material stock patterns determine levels of resource use and emissions to a similar extent as GDP does. Population density plays a smaller role than widely assumed, while neglecting material stock patterns in attempts to understand the determinants of cross-country differences in resource use and GHG is a serious omission. Our indicators are a good starting point for considering such patterns in future analyses, which could be useful in analyzing possibilities for decoupling resource use from GDP.

The material stock pattern indicator with the most consistent explanatory value across all analyses is built-up land per capita (BL_{cap}). This is plausible because infrastructures and buildings require energy for being built and used, which results in CO_2 emissions in current fossil-fuel dominated energy systems. Higher BL_{cap} also means larger floor size and more space between destinations, which all raises energy demand in buildings and transport. These findings corroborate previous analyses (using different models) suggesting that challenges for climate-change mitigation strongly depend on the future accumulation of additional material stocks in buildings and infrastructures[35–37]. This is worrying as material stocks are growing globally largely in unison with GDP[29,37]. In terms of the importance of specific spatial patterns, the analysis reveals that relationships found in urban-scale studies are also important at the national scale: high population densities in cities[25] and strong connectivity of urban transport infrastructures help reducing energy use and CO_2 emissions, whereas high dispersion of built-up land and large rural transport infrastructures drive them upwards.

While more research is warranted, our results have implications for countries pursuing ambitious climate targets[9]. In general, build-up of large material stocks is identified as a currently neglected driver of energy use and emissions. Efforts to ensure societal wellbeing while constraining land conversion to settlements and infrastructures help moving towards zero-carbon societies. Improved design of settlement and infrastructure

patterns – e.g., high connectivity with infrastructures favoring walking and cycling in cities – is commendable. Reducing fragmentation of landscapes and constraining urban sprawl, reducing expansion of highways and other investment in infrastructures that favor energy-intensive mobility patterns emerge as options that could help reducing energy use. These options could contribute to low-energy futures with high wellbeing[38] that would facilitate staying within a 1.5° global warming target without large-scale implementation of CO_2 reduction options such as bioenergy with carbon capture and sequestration[31].

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Declarations

Author contributions

HH conception of research design, data analysis, interpretation of results, article drafting, project management, funding acquisition, ML development of spatial indicators, spatial analyses, data analysis, quantification of indicators, designing figures, contribution to writing. APL conceptualization and implementation of statistical analyses, data analysis, designing figures, contribution to article writing, SM spatial and statistical analyses, data analysis and interpretation, contribution to writing, BP collation of STIRPAT indicators, data analysis and interpretation, contribution to writing, DW, FC, KHE contribution to

research design, data analysis and interpretation, contribution to writing, JAD conception and supervision of statistical analyses, research design, data analysis and interpretation, contribution to writing.

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Competing interests

The authors declare no competing interests

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Supplementary Information and Extended Data

This article includes supplementary information and Extended Data Figures.

Figures

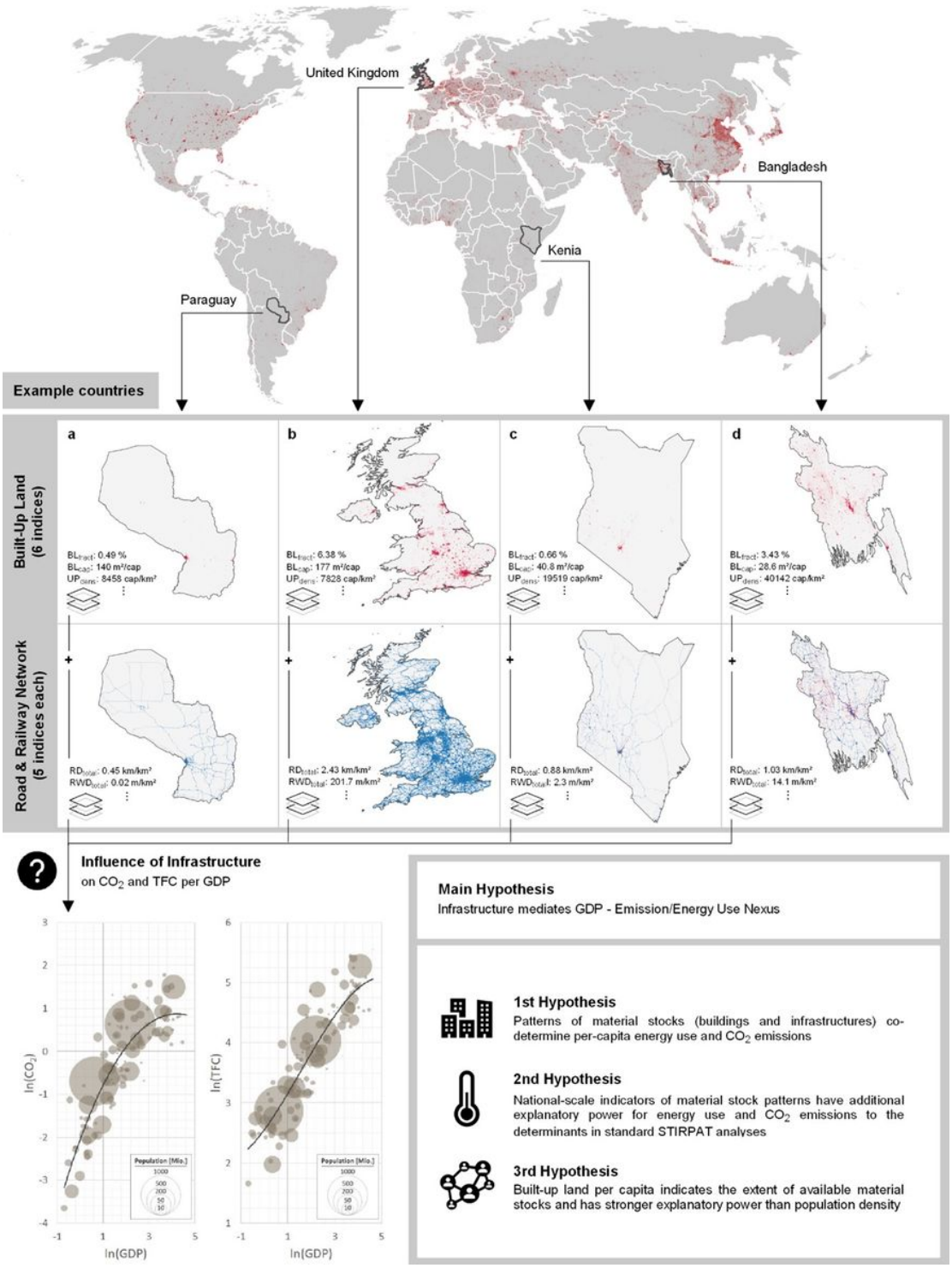

Figure 1

Workflow of this study. National-level indicators of the extent and spatial patterns of settlements and infrastructures ('material stock patterns') were derived from maps, illustrated using Paraguay, the UK, Kenia and Bangladesh as examples. Results were statistically analyzed along with STIRPAT factors usually assumed to co-determine energy use and CO_2 emissions. The main aim was to test the hypotheses formulated in the lower-right box.

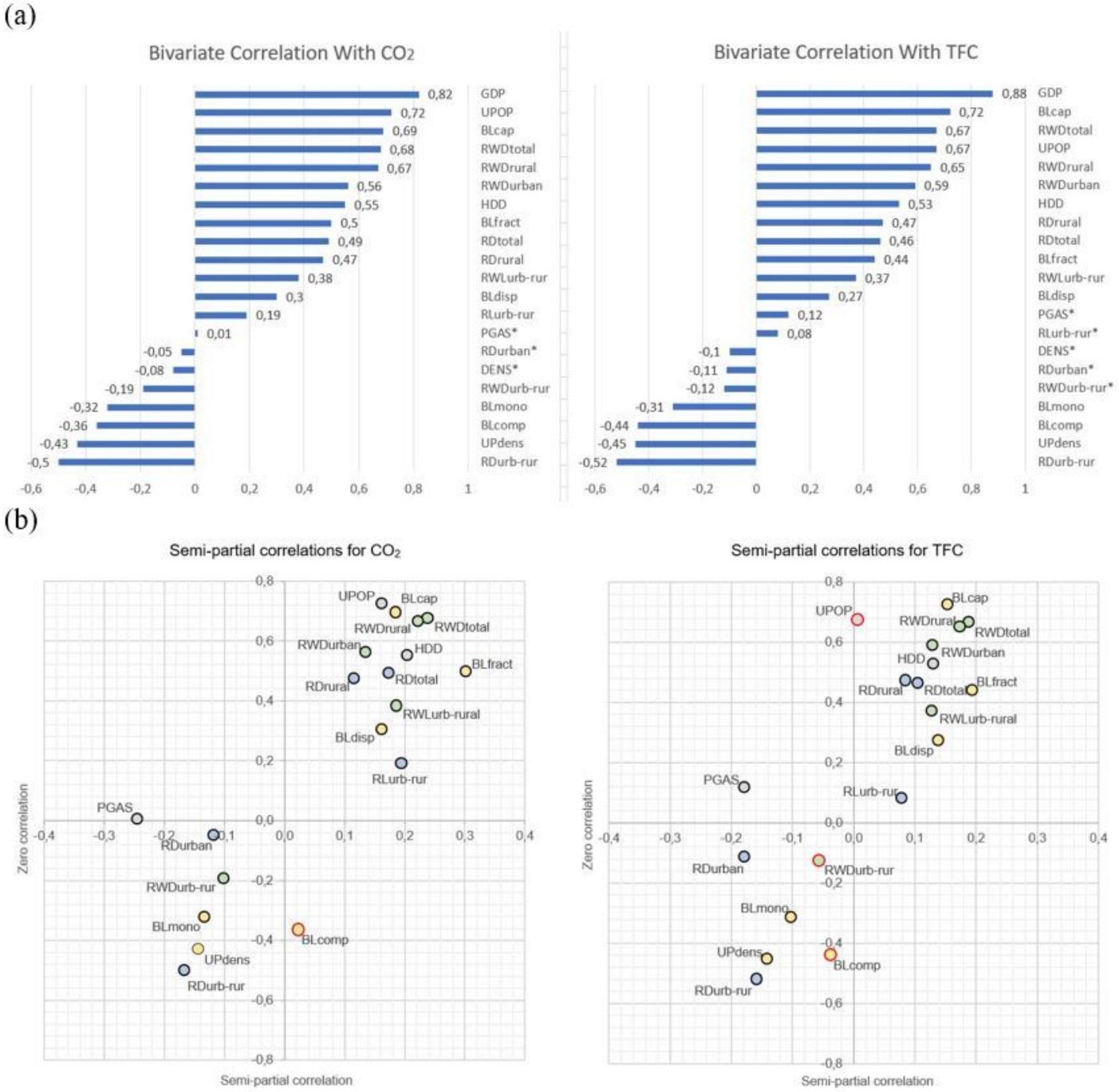

Figure 2

Correlation analyses of per-capita CO_2 emissions (CO_2) and total final energy use per capita (TFC) with STIRPAT and material stock pattern indicators. (a) Pearson's zero correlation coefficients of correlations between CO_2 (left) and TFC (right) and material stock pattern indicators as well as STIRPAT indicators. Natural logarithms of the variables were analyzed. Squaring the correlation coefficients gives the percentage of the cross-country variation of TFC or CO_2 explained by the respective indicator alone. Asterisks: not significant ($p<0.1$). (b) Semi-partial correlations between material stock pattern indicators and CO_2 (left) and TFC (right) controlling for GDP and DENS. Distance from the vertical axis indicates the correlation coefficient of the semi-partial correlation, and distance from the horizontal axis is the correlation coefficient of the bivariate (uncontrolled) correlation. Red contours indicate insignificant results (significance level $p<0.1$).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SuppInfo.docx
- ExtendedData.docx