Exploring the Built Environment–Circular Economy–Environmental Pressure Nexus: A Bayesian Network Approach

Esma Nur Cinicioglu[1](✉), Tatjana Tambovceva[2], and Evrim Celik Madenli[3]

[1] School of Business, Istanbul University, 34320 Avcilar, Istanbul, Türkiye
esmanurc@istanbul.edu.tr
[2] Institute of Sustainable Building Materials and Engineering Systems, Riga Technical University (RTU), Riga, Latvia
[3] Department of Civil and Environmental Engineering, University of Liverpool, Liverpool, UK

Abstract. The built environment is often treated as a driver of resource depletion, waste generation, and environmental harm. Yet this view is incomplete if it overlooks that the built environment is also shaped by engineering, design, and technological choice, and may therefore function not only as a source of pressure but also as a potential site of mitigation. This study examines that tension by asking whether the built environment operates mainly as a channel through which development-related pressures intensify environmental damage, or whether its links with circularity- and efficiency-related mechanisms also reveal mitigating pathways. To address this question, the paper employs a Bayesian Network framework using Eurostat data for the 27 European Union member states over the period 2014–2023. Based on pooled country-year observations, the analysis investigates the probabilistic dependency structure among indicators representing built environment activity, circular economy processes, and environmental pressure. In doing so, it provides an integrated and interpretable view of this nexus and illustrates the value of Bayesian Networks for analyzing interdependent sustainability indicators.

Keywords: Bayesian network · Built environment · Circular economy · Environmental pressure · Sustainability

1 Introduction

The built environment is often discussed as a major driver of resource depletion, waste generation, and environmental degradation. Yet this view is incomplete if the built environment is treated as an autonomous starting point. Its expansion is shaped by broader demographic and socioeconomic pressures. Rising population, increasing density, and higher levels of economic activity create demand for housing, infrastructure, and related services, thereby stimulating construction and intensifying the use of materials, energy, and land. The built environment is therefore not simply an exogenous force acting on the environment, but also a material outcome of development pressures that influences how those pressures are translated into environmental consequences.

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Accordingly, the environmental role of the built environment depends on how development pressures are materialized through construction, design, infrastructure, and resource-use patterns. When these patterns remain linear and resource-intensive, they may aggravate environmental pollution (Liang et al., 2019), increase pressure on urban water systems (Ganguly and Cahill, 2020), and contribute to rising CO_2 emissions (Wang and Zhao, 2018). However, as a domain shaped by engineering, design, planning, and technological choices, the built environment may also support mitigation when resilience and sustainability are embedded in infrastructure design and operation. Sánchez-Silva et al. (2025) emphasize that resilience and sustainability are central to the safe and responsible evolution of the built environment, including lifelines, road networks, energy supply, and housing. This mitigation potential is reflected in energy-efficient buildings, renewable energy integration, lower material intensity, improved resource productivity, circular construction practices, and reduced water demand.

The key issue, therefore, is not whether the built environment is inherently harmful or beneficial, but how its interaction with circular economy processes and environmental outcomes can be understood within a broader system perspective. This interaction is inherently multidimensional. Environmental implications arise through construction-related waste, domestic material consumption, material footprint, greenhouse gas emissions, and water stress, while mitigation may depend on resource productivity, renewable energy use, circular material use, recycling, and recovery mechanisms. Existing studies often approach these dimensions through composite indicators, urban quality-of-life frameworks, or building-level circularity assessment tools (Psatha, 2025; Khadim et al., 2025). Although these approaches are valuable, they generally focus on aggregated scores, individual dimensions, or isolated assessment structures. They therefore provide limited insight into how built environment activity, circularity-related mechanisms, and environmental pressures interact probabilistically within a broader system.

Given this multidimensional and interdependent structure, this study employs a Bayesian Network framework to examine the built environment–circular economy–environmental pressure nexus in the European Union. The analysis is based on 18 Eurostat variables covering demographic and macroeconomic conditions, construction activity, material and waste pressures, circularity mechanisms, mitigation-related factors, and environmental outcomes. Annual observations for 27 EU countries over 2014–2023 are pooled to identify the EU-level probabilistic dependency structure among these variables, rather than to conduct a country-by-country comparison. The purpose is to investigate how built environment activity is probabilistically positioned within this system and whether it is associated mainly with environmental pressure or also with circularity- and efficiency-related mitigation pathways. The remainder of the paper presents the methodology and dataset, the learned network and analyses, and the main findings and conclusions.

2 Methodology and Data

Bayesian Networks (BNs) are directed acyclic probabilistic graphical models in which nodes represent variables and directed arcs represent probabilistic dependencies. Each node is associated with a local probability distribution, marginal if it has no parents and

conditional if it does. Under the conditional independence assumptions encoded in the graph, the joint probability distribution can be factorized into the product of these local distributions, as shown in Eq. (1)

$$P(X_1, \ldots, X_N) = \prod_{i=1}^{N} P(X_i | Pa(X_i)) \quad (1)$$

BNs are well suited to complex multivariate systems because they allow dependency structures, indirect effects, and uncertainty propagation to be examined within a unified probabilistic framework. Their data-driven and interpretable structure has supported applications in civil and reliability engineering (Wang et al., 2025; Zwirglmaier et al., 2024), risk analysis (Arabi et al., 2022), economics and finance (Cinicioglu et al., 2024), and medicine (Bhardwaj et al., 2022). They have also been used to examine broader sustainability nexuses, such as the Water–Energy–Food–Economy–Society–Environment nexus (Chai et al., 2020), and EU circular economy indicator dependencies (Cinicioglu, 2025). However, their application to the built environment–circular economy–environmental pressure nexus remains limited. The empirical dataset was obtained from the Eurostat database (European Commission, 2026) and covered the period 2014–2023. The Bayesian Network was constructed using 18 variables grouped into six analytical dimensions: contextual drivers (population density, real GDP per capita); built environment activity (construction investment, construction employment, construction GVA); resource and waste pressures (domestic material consumption, construction waste generation, municipal waste generation per capita); circularity (CDW treatment recovery rate, trade in recyclable raw materials, recycling rate of municipal waste, circular material use rate); mitigation (resource productivity, renewable energy share, energy productivity); and environmental pressure/harm (material footprint, water exploitation index, greenhouse gas emissions). These dimensions capture the broader demographic and macroeconomic context, construction-related activity, material and waste pressures, circularity mechanisms, mitigation capacity, and environmental outcomes associated with the system under study. The analysis covered the 27 EU countries for which continuous annual data were available over the full period. Each country-year was treated as one observation, yielding 270 observations per variable. The purpose was therefore not to conduct a country-by-country comparison, but to identify the EU-level probabilistic dependency structure among the selected variables and explore the relationships within the built environment–circular economy–environmental pressure nexus. The few missing observations were completed through simple within-country imputation using neighboring observations from the same country series.

Before model estimation, all variables were discretized into four ordinal states using hierarchical discretization, with thresholds determined separately for each variable according to its empirical distribution. Four states were preferred to balance interpretability and distributional differentiation. Hierarchical discretization was used because it allows state boundaries to emerge from each variable's empirical structure rather than from arbitrary cut-off values, thereby preserving variable-specific distributional characteristics. The structure of the Bayesian Network was then learned from the data using the Bayesian Search algorithm, a score-based method employing hill-climbing optimization with random restarts to identify the network structure maximizing the log-likelihood score (Bouckaert, 1995; Cooper and Herskovits, 1992). The associated

conditional probability distributions were subsequently estimated using the Expectation–Maximization (EM) algorithm, which iteratively estimates the conditional probability tables by maximizing the likelihood of the observed data given the learned network structure (Dempster et al., 1977; Lauritzen, 1995). All procedures were carried out in GeNIe 5.0 (BayesFusion, 2025).

3 Analysis and Results

Figure 1 presents the Bayesian Network obtained from the procedure described in the previous section. It represents the data-driven dependency structure of the built environment–circular economy–environmental pressure nexus. Variables are color-coded according to the six analytical dimensions to facilitate interpretation: yellow for contextual drivers, blue for built environment activity, purple for resource and waste pressures, green for circularity, orange for mitigation, and red for environmental pressure/harm. Each node displays its marginal probability distribution across the four discretized states, where $s1$ denotes the lowest value interval and $s4$ the highest. The interval labels preserve interpretability with respect to the original variable scales. The resulting network contains 44 arcs, representing direct probabilistic dependencies among the variables; however, these dependencies differ in strength.

Arc thickness in Figure 1 represents the strength of the corresponding parent–child relationship. In this study, arc strength was quantified by the average Euclidean distance between the child node's conditional probability distributions across the states of its parent. Let X and Y denote two variables in the BN, where X is the parent node and Y is the child node. For each parent state x_i, let $P(Y \mid X = x_i)$ denote the conditional probability vector of Y. The Euclidean distance between two conditional distributions of Y, corresponding to two different parent states x_i and x_j, is computed as in (2) where k denotes number of discrete states of the child variable Y. The arc strength is then obtained by averaging this distance over all pairs of parent states. Larger values indicate stronger changes in the child node's conditional distribution as the parent node moves across its states. Table 1 reports the five strongest relationships based on average arc strength.

$$d\left(x_i, x_j\right) = \sqrt{\sum_{m=1}^{k} \left[p(y_m|X = x_i) - p\left(y_m|X = x_j\right)\right]^2} \tag{2}$$

The strongest average arc strengths are observed between Material Footprint and Domestic Material Consumption (0.4964), Real GDP per capita and Domestic Material Consumption (0.4437), and Water Exploitation Index and Population Density (0.3765). These relationships indicate that the strongest probabilistic dependencies in the network are associated with broader patterns of material consumption, economic activity, and population-related pressure rather than directly with built environment activity variables. In particular, the strong dependency between Material Footprint and Domestic Material Consumption highlights the central role of consumption intensity within the nexus.

The arc structure also provides important insights into the role of built environment activity. The three built environment activity variables, namely Construction Investment, Construction Employment, and Construction Gross Value Added, do not exhibit

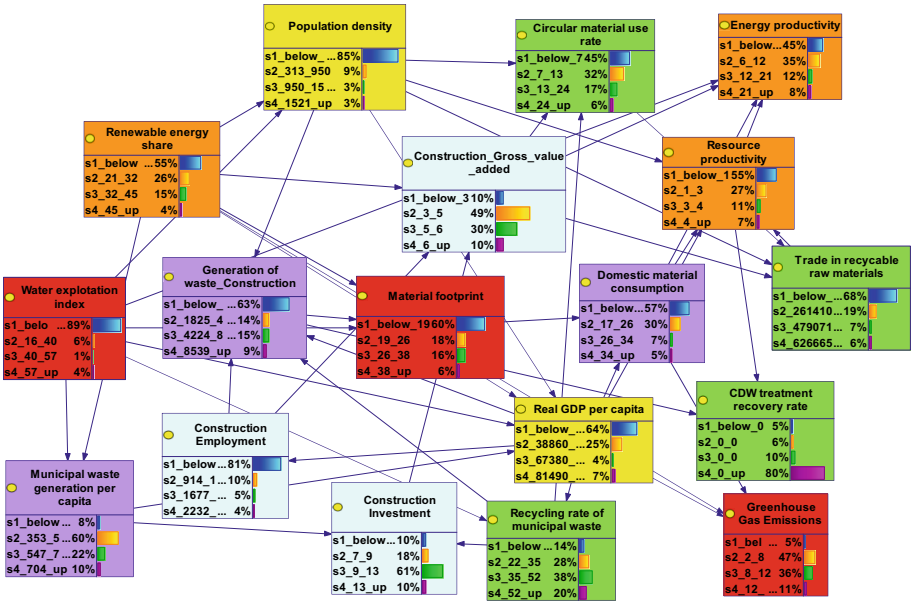


Fig. 1. Learned Bayesian Network with arc thickness indicating arc strength

Table 1. Top five parent–child relationships by average arc strength

Parent node	Child node	Average arc strength
Material footprint	Domestic material consumption	0.496399
Real GDP per capita	Domestic material consumption	0.4437
Water exploitation index	Population density	0.376494
Recycling rate of municipal waste	Construction Investment	0.350131
Renewable energy share	Municipal waste generation per capita	0.332998

direct probabilistic dependencies with the environmental pressure/harm variables. On the contrary, their direct dependencies are observed with construction-related, circularity-related, and mitigation-related variables. Construction Employment is directly connected to Construction Gross Value Added (0.2007) and Generation of Waste–Construction (0.0589). Construction Investment is directly connected to Construction Gross Value Added (0.2006), while it is also linked with Recycling Rate of Municipal Waste (0.3501) and Municipal Waste Generation per capita (0.3203). Construction Gross Value Added is directly connected to Trade in Recyclable Raw Materials (0.1344), Circular Material Use Rate (0.1167), and Energy Productivity (0.0778). This pattern is important because, rather than positioning built environment activity directly as a probabilistic driver of environmental harm, the learned network associates it with construction dynamics,

circularity-related mechanisms, and mitigation-oriented variables. The direct dependency between Construction Gross Value Added and Energy Productivity is particularly noteworthy because Energy Productivity is included as a mitigation variable. This suggests that built environment activity may also be linked to efficiency-oriented processes rather than only to resource-intensive pressures. Likewise, its direct connection with Trade in Recyclable Raw Materials may indicate that material recovery and recirculation mechanisms are becoming integrated into construction-related economic activity. Taken together, these findings support the view that the role of the built environment within the nexus is multidimensional rather than unidirectional.

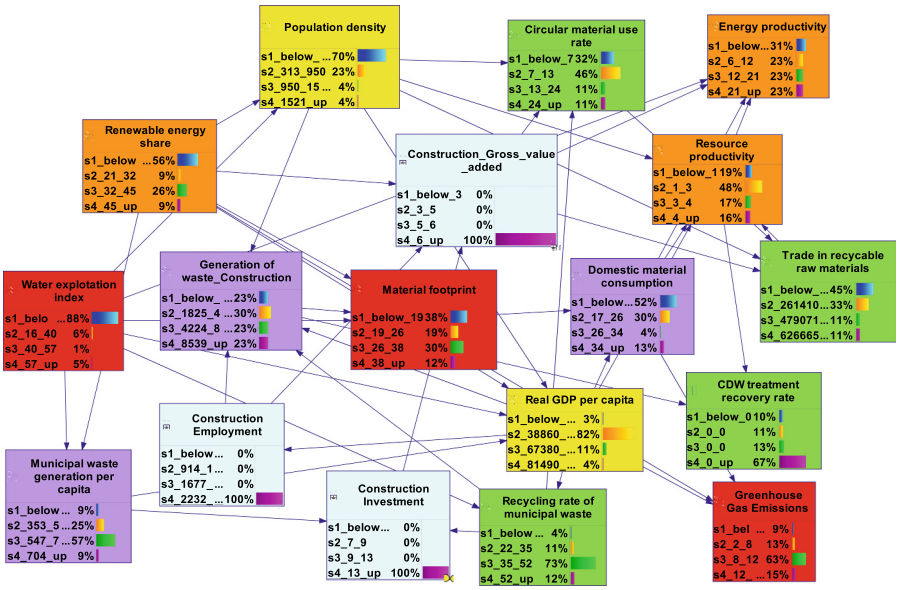


Fig. 2. Posterior probabilities of the Bayesian Network under high built environment activity, conditional on the evidence configuration Construction Gross Value Added = $s4$, Construction Investment = $s4$, and Construction Employment = $s4$

As the next step of the analysis, evidence observation was used to examine how the probability distribution of the remaining variables changes when a specific node or set of nodes is fixed to a given state. In probabilistic terms, this corresponds to conditioning the network on an entered evidence configuration, so that the posterior probability of a target variable is updated as $P(Y|E = e) = P(Y, E = e)\,/P(E = e)$. In the present analysis, the three built environment activity variables, namely Construction Gross Value Added, Construction Investment, and Construction Employment, were fixed at their highest state ($s4$). This evidence configuration is particularly informative because the learned network does not include direct arcs from built environment activity variables to the environmental pressure/harm variables. However, the absence of direct arcs does not imply that changes in the distributions of built environment activity variables are irrelevant for environmental pressure outcomes. In a Bayesian Network, probabilistic

influence may propagate through indirect paths, so conditioning one part of the network can update the posterior distributions of variables that are not directly adjacent to the evidence nodes. As shown in Fig. 2, the posterior distributions shift toward higher environmental pressure states. The most notable change is observed for Greenhouse Gas Emissions, where the probability of $s3$ increases from 36% to 63% and that of $s4$ increases from 11% to 15%. Material Footprint also shifts upward, with its distribution changing from 60%, 18%, 16%, and 6% to 38%, 19%, 30%, and 12% across states $s1$–$s4$. These findings indicate that, even in the absence of direct probabilistic dependencies, high built environment activity is still associated with stronger environmental pressure patterns through the broader dependency structure of the network, reflecting its role as an interface between socioeconomic development pressures and environmental outcomes.

4 Conclusions

The results show that the built environment cannot be interpreted as a simple direct source of environmental harm. In the learned network, built environment activity variables do not exhibit direct dependencies with environmental pressure/harm variables; instead, their direct links are mainly observed with circularity- and mitigation-related variables such as Circular Material Use Rate, Trade in Recyclable Raw Materials, Recycling Rate of Municipal Waste, and Energy Productivity. However, evidence observation indicates that high built environment activity still shifts the system toward stronger environmental pressure patterns, particularly through higher posterior probabilities for Greenhouse Gas Emissions and Material Footprint. This suggests that the built environment operates as an interface between socioeconomic development pressures and environmental outcomes, rather than as an isolated driver of harm. Overall, the findings support the need to understand the built environment–circular economy–environmental pressure nexus as a multidimensional and probabilistically interdependent system. Bayesian Networks are therefore useful for tracing both direct dependencies and indirect posterior shifts within this system.

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