Mapping Material Stocks and Embodied Greenhouse Gas Emissions in Norwegian Residential Buildings

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I declare that this document is an original work of my own authorship and that it fulfils all the requirements of the Code of Conduct and Good Practices of the *Universidade de Lisboa*.

Abstract

Reliable data on material stocks and related emissions in residential buildings is lacking at national and municipal scales in Norway, which limits the ability to plan resource management and climate mitigation policies. This thesis addresses this gap by quantifying material stocks and embodied greenhouse gas emissions in Norwegian residential buildings at the municipal level. Material intensities were compiled for construction cohorts and building types and combined with data on dwellings, buildings and heated floor area. To address data uncertainty, Monte Carlo simulations were applied using triangular probability distributions based on minimum, maximum and mode values. Results show that concrete surrogate dominates material stocks with 139.3 Mt nationwide, followed by wood and wood products with 43.8 Mt and concrete with 39.8 Mt. Despite lower stock, construction-grade steel accounts for the highest production-related emissions with 21.8 Mt CO_2e, while wood and wood products contribute 5.35 Mt CO_2e and concrete surrogate only 0.56 Mt CO_2e. Municipal-level analysis reveals that rural areas with low population density and a predominance of single-family houses exhibit the highest per-capita emissions. Principal Component Analysis shows socio-economic and geographic patterns, with education, income and latitude associated with material stocks and emissions. This study provides a reproducible methodological framework for consistent, spatially explicit analysis and comprehensive dashboard to support municipal and national decisions on resource management and climate policy.

Keywords

methodological framework, material stock mapping, embodied carbon emissions, residential stock, uncertainty quantification

Resumo

A disponibilidade de dados fiáveis sobre stocks de materiais e emissões associadas a edifícios residenciais na Noruega é limitada, tanto a nível nacional como municipal, o que restringe a capacidade de planear a gestão de recursos e as políticas de mitigação climática. Esta tese aborda essa lacuna quantificando os stocks de materiais e as emissões incorporadas de gases com efeito de estufa em edifícios residenciais noruegueses à escala municipal. Para tal, foram compiladas intensidades de materiais por coortes de construção e tipos de edifícios, combinadas com dados sobre fogos, edifícios e área útil aquecida. Para lidar com a incerteza dos dados, aplicaram-se simulações de Monte Carlo com distribuições triangulares baseadas em valores mínimos, máximos e modais. Os resultados indicam que o betão substituto domina os stocks de materiais com 139,3 Mt a nível nacional, seguido da madeira e derivados (43,8 Mt) e do betão convencional (39,8 Mt). Apesar de representar o menor stock, o aço de construção é responsável pelas emissões mais elevadas associadas à produção (21,8 Mt CO_2e), enquanto a madeira e derivados contribuem com 5,35 Mt CO_2e e o betão substituto apenas com 0,56 Mt CO_2e. A análise ao nível do município mostra que áreas rurais, com baixa densidade populacional e predominância de moradias unifamiliares, apresentam as emissões per capita mais elevadas. A Análise de Componentes Principais evidencia padrões socioeconómicos e geográficos, associando educação, rendimento e latitude a stocks e emissões. Este estudo disponibiliza uma metodologia reprodutível para análises consistentes e espacialmente explícitas, complementada por um painel interativo de apoio às decisões municipais e nacionais em matéria de gestão de recursos e política climática.

Palavras-chave

quadro metodológico, mapeamento de stocks de materiais, emissões incorporadas de carbono, parque habitacional, quantificação da incerteza

Resumo Alargado

O ambiente construído constitui um dos principais e mais persistentes motores do uso de materiais e das emissões de gases com efeito de estufa (GEE) a nível global. Os edifícios residenciais, em particular, representam uma componente central dos stocks nacionais de materiais, e as emissões incorporadas associadas têm sido cada vez mais reconhecidas como um obstáculo crítico à neutralidade climática. Apesar da relevância deste setor, persiste a ausência de análises de alta resolução sobre os stocks de materiais de construção e as respetivas emissões, capazes de orientar a gestão de recursos e o desenho de políticas a nível local na Noruega. Estudos globais e regionais têm avançado na quantificação dos stocks e fluxos do ambiente construído, mas frequentemente tratam as estruturas antrópicas como uma categoria indiferenciada, não captando as variações entre tipos de edifícios nem entre coortes de construção a escala municipal. Para a Noruega, um país com fortes ambições de sustentabilidade, sistemas estatísticos detalhados e padrões de povoamento diversificados, esta lacuna representa simultaneamente um desafio e uma oportunidade.

O objetivo do presente estudo foi quantificar a distribuição e composição dos stocks de materiais nos edifícios residenciais dos municípios noruegueses e estimar as emissões incorporadas de GEE, resultantes quer da produção de materiais, quer da própria construção, respondendo a quatro questões de investigação relativas à escala, composição, incerteza e padrões regionais.

Para responder a estas questões, foi desenvolvido, testado e refinado um fluxo metodológico abrangente. A base da análise consistiu em dados municipais sobre área útil aquecida das habitações, diferenciados por tipologia de edifício e coorte de construção. Estes dados foram combinados com valores de intensidade material provenientes de estudos prévios, que fornecem estimativas de quantidades de material por metro quadrado de área útil aquecida. Foram exploradas várias opções metodológicas, incluindo a desagregação de habitações em edifícios e a conversão de números de fogos em áreas estimadas. Após testes, a abordagem mais robusta revelou ser a utilização direta da área útil aquecida municipal multiplicada pelas intensidades materiais, garantindo comparabilidade com a literatura e consistência interna entre municípios. Esta opção reduziu potenciais fontes de erro e permitiu integrar fatores de emissões incorporadas tanto da produção de materiais como do consumo energético na construção.

Um desafio relevante foi a ausência de intervalos de incerteza nos dados brutos disponíveis. Para mitigar este problema, aplicaram-se simulações de Monte Carlo, gerando intervalos plausíveis para os stocks de materiais e emissões incorporadas. As distribuições foram escolhidas segundo o princípio da entropia máxima, evitando uma falsa sensação de precisão. Quando existiam valores mínimo, máximo e moda, utilizaram-se distribuições triangulares. Este enquadramento probabilístico enriqueceu os resultados, substituindo valores determinísticos únicos por representações mais nuançadas da variabilidade municipal, que mostram a variabilidade dos dados em cada município, conferindo maior robustez à análise da variabilidade entre municípios

Uma vez que nem todos os dados sobre gastos energéticos se encontravam diretamente disponíveis, foi necessário estimar os requisitos de energia para a construção. Valores específicos foram extraídos da literatura, convertidos para unidades apropriadas e incorporados na análise. Os vetores energéticos foram associados a diferentes tipos de edifício. Para evitar cenários irrealistas nas simulações, calcularam-se primeiro as quotas originais de materiais e vetores energéticos, aplicando-as depois às distribuições simuladas, prevenindo distorções como edifícios com combinações materiais improváveis.

Os resultados revelaram vários aspetos importantes. Em termos de stock total de materiais, o betão (ou substituto equivalente) foi dominante, com cerca de 139,3 Mt a nível nacional, sobretudo em edifícios mais antigos construídos em meados do século XX e em moradias unifamiliares. Contudo, devido à relativamente baixa intensidade carbónica do betão, a sua contribuição para as emissões foi limitada. O aço de construção, pelo contrário, representou menor volume de stock mas surgiu como principal fonte de emissões incorporadas, estimadas em 21,8 Mt CO_2e. Este resultado sublinha o impacto desproporcionado de materiais com elevada intensidade carbónica, mesmo em menores quantidades.

Geograficamente, os stocks de materiais e emissões mostraram padrões espaciais claros. As maiores quantidades absolutas concentraram-se nos municípios mais populosos, incluindo Oslo, Bergen, Trondheim e Tromsø, refletindo a ligação entre densidade populacional e atividade construtiva. Porém, quando normalizados *per capita*, emergiu uma realidade distinta: municípios rurais, com baixa densidade populacional e predominância de habitações unifamiliares, registaram os valores mais elevados de emissões incorporadas *per capita*, entre 13,7 e 17 tCO_2e por pessoa. Este contraste evidencia o duplo desafio de reduzir tanto as emissões agregadas nos centros urbanos como os impactos per capita nas áreas rurais.

A análise estatística mostrou ainda forte correlação entre o total do stock material e as emissões incorporadas, captada através de análise de componentes principais. Isto indica que áreas com maior intensidade material tendem também a apresentar emissões mais elevadas, confirmando a ligação estrutural entre acumulação de materiais e impacto ambiental. Além disso, a desagregação das emissões demonstrou que a produção de materiais domina amplamente face às emissões de construção, embora estas últimas se mantenham relevantes em tipologias específicas. Para apoiar a comunicação dos resultados, foi desenvolvido um painel interativo (*dashboard*) que permite explorar os dados a diferentes escalas (nacional e municipal) e cenários (médio, otimista, pessimista), com base nas distribuições Monte Carlo. Esta ferramenta torna os resultados acessíveis a decisores, planeadores e investigadores, promovendo decisões baseadas em evidência.

Apesar da robustez metodológica, o estudo apresenta limitações. A principal prende-se com a disponibilidade restrita de dados geográfica e temporalmente específicos para a Noruega. As intensidades materiais e energéticas foram muitas vezes baseadas em fontes internacionais, podendo não refletir totalmente as condições locais, sobretudo em coortes mais antigas. Outra limitação foi a ausência de intervalos de incerteza na maioria dos dados de entrada, exigindo suposições sintéticas nas simulações, o que pode ter introduzido enviesamentos. Além disso, algumas categorias materiais, como metais não estruturais, betume e gesso, foram excluídas devido à sua reduzida representatividade e elevada incerteza nos fatores de emissão, podendo originar uma ligeira subestimação das emissões totais.

Estes limites abrem caminhos para investigação futura: (i) desenvolvimento de bases de dados históricas mais específicas para a Noruega; (ii) alargamento da análise a outros impactes ambientais além dos GEE, como perda de biodiversidade ou toxicidade; (iii) aplicação da metodologia a outros países com infraestruturas estatísticas comparáveis; e (iv) modelação dinâmica da renovação do parque edificado, antecipando fluxos futuros de materiais e resíduos e oportunidades de economia circular.

Em síntese, este estudo demonstra que uma abordagem de alta resolução a nível municipal pode gerar conhecimento valioso sobre a composição material do setor residencial e as emissões incorporadas associadas. A conjugação de dados municipais de área útil aquecida com intensidades materiais diferenciadas e simulações probabilísticas permitiu produzir estimativas robustas, alinhadas com a literatura mas com maior granularidade. Os resultados destacam os desafios estruturais e as oportunidades para reduzir emissões, sublinhando a importância da substituição e eficiência de materiais de elevada intensidade carbónica como o aço, bem como da necessidade de políticas diferenciadas entre contextos urbanos e rurais. O painel interativo aumenta a utilidade prática do trabalho, facilitando a integração dos resultados em processos de decisão.

Conclui-se que a metodologia e resultados apresentados avançam o conhecimento sobre análise de stocks de edifícios em alta resolução na Noruega, oferecendo também um quadro reprodutível para outros países. O estudo fornece uma base para investigação e políticas orientadas à redução de emissões incorporadas e ao uso sustentável de materiais no setor residencial. Ao articular avaliações globais com realidades locais, evidencia-se o valor de abordagens espacialmente explícitas e informadas pela incerteza para gerir os impactes ambientais do ambiente construído, na Noruega e além-fronteiras.

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List of Abbreviations

AB	Apartment Block
CI	Carbon Intensity
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
CSV	Comma-Separated Values
EI	Energy Intensity
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
GWP100	Global Warming Potential over a 100-year period
HFA	Heated Floor Area
INE	National Statistics Agency
IPCC	Intergovernmental Panel on Climate Change
Kt	Kiloton
LCA	Life Cycle Assessment
LCIA	Life-cycle Impact Assessment
LiDAR	Light Detection and Ranging
LLM	Large Language Model
MFH	Multi-family House
MJ	Megajoule
MSA	Material Stock Analysis
Mt	Megaton
NUTS	Nomenclature of Territorial Units for Statistics
ODYM-RECC	Open Dynamic Material Systems for Resource Efficiency and Climate Change
PC1	The first principal component in Principal Component Analysis
PC2	The second principal component in Principal Component Analysis
PCA	Principal Component Analysis
PDF	Portable Document Format
SFH	Single-family House
SHP	Shapefile
TH	Terraced House

List of Symbols

$A_{i,j}$	Total material stock of material type i per archetype j [kg]
D_i	Direct CO_2 emissions resulting from the production of a material type i [kg CO_2e]
D_k	Direct CO_2 emissions resulting from the use of energy carrier k [kg CO_2e]
$E_{int,j,k}$	Energy intensity of manufacturing per unit area of archetype j using energy carrier k [MJ/m²]
$E_{j,k}$	Total energy demand for manufacturing the heated floor area of archetype j using energy carrier k [MJ]
E_k	Energy demand associated with energy carrier k [MJ]
F_k	Carbon intensity (CI) for energy carrier k, representing direct CO_2e emissions per unit of energy [kg CO_2e/MJ]
GWP_i	Global Warming Potential 100 (GWP100) [kg CO_2e/kg]
M_i	Total mass of material type i in the municipality [kg].
$MI_{i,j}$	Material inventory of material type i per building of archetype j [kg]
$M_{int,I,j}$	Material intensity of material type i per building of archetype j [kg/m²]
N	Number of dwellings
$S_{av,j}$	Average heated floor area per dwelling of archetype j [m²]
$S_{total,j}$	Total heated floor area of archetype j in the municipality [m²]

List of Software

Jupyter Notebook	Environment for interactive coding and documenting workflows
pandas	Python library for data manipulation
numpy	Python library for numerical computations
matplotlib	Python library for data visualizations
seaborn	Python library for data visualizations
plotly	Python library for interactive visualizations
geopandas	Python library for handling geospatial data
scikit-learn	Python library for statistical analysis and PCA
dash	Python library for building interactive dashboard
statsmodels	Python library for statistical modelling
json	Python library for files configuration and data interchange
plotly.express	Python library for high-level interface with interactive visualizations
QGIS	Platform for spatial data exploration
GitHub	Code repository for version control and code sharing
Excel	Software for initial tabular data review
Python (3.11.5)	Programming language for data analysis and dashboard development

1. Introduction

1.1 Overview and motivation

Material production accounts for more than half of industrial greenhouse gas (GHG) emissions, therefore strategies focused on material efficiency and the circular economy are crucial to mitigate these emissions (Hertwich 2021). The transition towards a more sustainable and resource-efficient built environment requires a deeper understanding of how materials are distributed and used in buildings and of the emissions that result from their production and construction (Haberl et al. 2025). Residential buildings form a large part of the urban infrastructure in Norway (SSB Building Stock 2025; Rousseau et al. 2025), and material composition, construction and maintenance of buildings have huge implications for environmental impacts and resource flows (Tanikawa et al. 2021).

Recent studies have focused on material stock analysis and the environmental footprint of the construction sector (Lausselet et al. 2020; Rousseau et al. 2025; Sartori et al. 2016), however, many of them remain limited in spatial granularity. In particular, linking material intensities with actual residential building stocks at a detailed geographic level, such as municipalities, can significantly improve our ability to identify regional patterns and support climate targets at national and local levels.

Norway offers a compelling case for this kind of analysis. The country's open and comprehensive statistical datasets, together with its strong sustainability ambitions (Ministry of Climate and Environment 2021), create an ideal setting to explore high-resolution stock and emissions analysis. Previous studies were have estimated these metrics at neighbourhood (Lausselet et al. 2020), region (Rousseau et al. 2025) and national (Sartori et al. 2016) scale. However, challenges remain, especially due to differences in how residential building and dwelling data are reported by different organizations and sources, and how material and carbon intensities are applied. This calls for a harmonised approach that can coherently connect these layers of data.

This study adapts and applies methodologies of material stock and embodied emissions modelling to the Norwegian context at the municipal level. It combines statistical and geospatial datasets with life cycle inventory data and incorporates probabilistic modelling to address uncertainties. Beyond enabling a detailed analysis of Norway's residential building stock, the approach provides a transferable framework that can support the development of visualization platforms and decision-support tools. By integrating structured datasets and uncertainty analysis, the framework allows for the examination of material stocks and emissions across different spatial and temporal scales. While no fully established ontology for this domain was identified, the study draws on relevant conceptual structures to ensure consistency. Importantly, the approach is adaptable and can be applied in other contexts where comparable data are available, thus facilitating cross-regional benchmarking and informing sustainability-oriented interventions.

1.2 Objective and research questions

Material production and the construction sector are among the largest contributors to global greenhouse gas (GHG) emissions ("EBC Annex 57 Results," 2016). Gaining insight into spatial distribution of materials and embodied emissions is essential for identifying effective strategies to reduce this environmental footprint. This knowledge supports the implementation of circular economy principles and enhances material efficiency practices across the built environment (Schiller et al. 2025).

The objective of this thesis is to analyse the distribution and composition of material stocks in residential buildings across Norwegian municipalities and to assess the embodied GHG emissions associated with material production (raw material extraction, transport, manufacturing) and building manufacturing (construction and installation processes), with an emphasis on ensuring that the results can be visually communicated and the approach can be replicated in future studies and applied in different contexts.

To address this aim, the following research questions were formulated:

1. What materials make up Norway's residential building stock, how are they distributed by municipality, and which materials, typologies and cohorts dominate?
2. Which materials, typologies, cohorts and energy carriers drive the most embodied GHG emissions in Norway's residential sector?
3. What are the total embodied GHG emissions from Norway's residential buildings, how are they geographically distributed, and how do they vary per capita and per heated floor area?
4. How can spatial and categorical patterns of material stocks and embodied emissions be communicated via an interactive dashboard to support different user needs and decisions, and how can the analytical framework be replicated elsewhere?

2. Literature Review

2.1 GHG emissions from material production

According to the Intergovernmental Panel on Climate Change (IPCC) (Shukla et al. 2022), global greenhouse gas (GHG) emissions rose significantly between 1990 and 2019, increasing from approximately 38 gigatons (Gt) to 59 Gt of CO_2-equivalent emissions. CO_2-equivalents (CO_2e) are a standard metric for GHG that convert the impact of gases like methane, nitrous oxide and other minor GHGs into the equivalent amount of CO_2 that would cause the same level of climate forcing over a 100-year time horizon. Among the main contributors to global emissions, material production stands out as one of the largest sources of industrial GHG emissions, accounting for over half of the sector’s total footprint. Emissions from material production have increased significantly, rising by 120% from 5 billion metric tons $GtCO_2e$ in 1995 to 11 $GtCO_2e$ in 2015 (Hertwich 2021). This rapid growth underscores the urgency of addressing material-related emissions through improved production processes, material substitution and circular economy strategies.

The continued increase in GHG emissions must be limited to avoid the most severe consequences of climate change. According to IPCC, historical GHG emissions from human activities have already led to a global temperature rise of approximately 1.1°C above pre-industrial levels (*AR6 Synthesis Report* 2023). The Paris Agreement sets a target to limit this increase to 1.5°C, which requires all sectors, including the building sector, to adopt effective mitigation strategies (IPCC 2022; Rogelj et al. 2018; Grubler et al. 2018; Camarasa et al. 2022).

2.1.1 Emissions from construction materials

A closer examination of sector-specific emissions reveals that certain construction materials contribute disproportionately to overall emissions. Carbon-intensive materials such as iron, steel, cement, lime, rubber and plastics are particularly significant. In 2011, cement, lime and plaster used in construction alone accounted for approximately 2.5 $GtCO_2e$, and iron and steel used in manufacturing contributed a comparable amount, around 2.4 5 $GtCO_2e$. The construction sector is also the primary destination for other high-emission materials such as non-metallic minerals (e.g., glass), wood, lead, zinc and tin. In addition to it, manufacturing heavily relies on rubber, plastics, and various metals like aluminium, copper and other non-ferrous materials (Hertwich 2021).

Overall, materials contribute to roughly 70% of the carbon footprint of construction, emphasizing the critical role of material choice and management in achieving emission reduction targets in the built environment (Hertwich 2021).

2.1.2 Emissions in the Norwegian context

In Norway, emissions from the construction sector are substantial (Ministry of Climate and Environment

2021), though lower in absolute terms compared to global figures due to the country's smaller population and stock size. According to the Norwegian Ministry of Climate and Environment (Ministry of Climate and Environment 2021), Statistics Norway (SSB, 2025) estimates that direct annual emissions from construction activities (including machinery use, heating and drying) are around 2 Mt CO_2e. At the same time, The Climate Footprint of Norwegian Economic Activity (CaFEAN) reports that in 2021, domestic construction and construction works contributed 1.81 Mt CO_2e to the footprint of Construction. These values do not account for embodied emissions from construction material production, which highlights the importance of integrating material-specific data into national emissions accounting. As one of the approaches to address this gap, researchers have proposed the use of representative building archetypes to estimate typical material compositions and quantities, thereby enabling more accurate assessments of embodied emissions (Röck et al. 2022). Archetypes also reflect regional construction characteristics and material preferences, offering a valuable basis for building and material stock analysis (Akin et al. 2023).

2.2 Norwegian residential building stock

There is a growing need to improve our understanding of the potential for expanding circular practices within the construction sector, particularly by accounting for the impact of local building stock characteristics and its spatiotemporal dynamics. For instance, future renovation and demolition activities are closely related to the age distribution of the building stock, which affects the availability of materials suitable for reuse (Sandberg et al. 2014b; Sartori et al. 2016; Sandberg et al. 2014a). Additionally, significant rural-urban disparities in future material demand are expected due to continued population growth in urban areas. This may result in a spatial mismatch between the locations of material demand and the availability of secondary materials (Berrill and Hertwich 2021). These dynamics remain insufficiently explored, and ongoing research aims to bridge these critical knowledge gaps.

The building sector, including both residential and non-residential structures, serves as a critical link between human well-being and environmental pressures, operating within a cascade of material services and presenting multiple opportunities for decoupling economic development from resource use and environmental degradation (Tanikawa et al. 2021). As of 2025, residential buildings create a substantial share (around 36%) of total Norwegian building stock (SSB Building Stock 2025). Given this significant proportion, it is crucial to assess the material stocks associated with residential construction and the embodied emissions linked to both material production and building activity. Besides, accurately modelling national building stocks helps identify opportunities for emission reduction and material efficiency (Akin et al. 2023).

2.2.1 Building types in Norwegian residential buildings

A proper classification of residential building types enables holistic comparison of material composition, space heating demand and other important parameters across various typologies and construction cohorts. To accurately track material flows and energy use of products throughout their life cycles, 21 archetypes have been developed to describe Norwegian residential building stock based on three typologies: single-family house (SFH), multi-family house (MFH) and apartment block (AB). These were further divided into seven construction cohorts corresponding to the time period when the residential building was constructed, spanning from before 1955 to 2020 (Amini et al. 2024; Pauliuk 2024).

This classification incorporates key parameters such as building geometry, construction techniques, thermal properties and other technical characteristics (Amini et al. 2024). The aggregation by type and construction period is essential for accurately estimating material types and quantities, as both technological advancements and material availability have shifted over time, influencing construction practices and material composition.

2.2.2 Material composition in Norwegian residential buildings

Approximately 85% of the Norwegian dwelling stock used to consist of small houses, predominantly constructed with wood as the primary building material. However, since the late 19th century, the introduction and growing use of concrete have significantly shifted building practices. Over the past 70-80 years, concrete has gained prominence due to its favourable material properties, enabling the cost-effective construction of larger and more durable buildings. This shift coincided with increasing urbanization and rising demand for higher-density housing within limited urban space. As a result, the use of wood in residential construction has gradually declined, particularly in multi-unit and urban developments (Bergsdal et al. 2007).

A detailed understanding of material composition is necessary when assessing material stocks and embodied emissions at the national scale. This includes identifying which specific material types contribute most significantly within different structural elements (e.g., structural wood, timber doors, wall components) (Loli et al. 2023). This also requires accounting for variation in elements and material composition between the building types and cohorts mentioned in the previous chapter.

According to the findings of Amini et al. (2024), material composition of residential buildings in Norway varies by building typology but is generally dominated by concrete. Across all mentioned archetypes, concrete accounts for over 45% of total material mass, and this dominance is largely due to its high density (up to 2,400 kg/m^3) and load-bearing structural role in buildings. In apartment blocks, most concrete is used in floor structures, while in single-family houses and multi-family houses, a large share is found in foundations and basement elements and often termed "surrogate concrete." In SFH and MFH, this surrogate concrete can represent over 40% and 30% of total mass, respectively. Wood ranks second in SFH and MFH types and is present in walls, floors, roofs, doors and window frames. In contrast, its share is below 10% in ABs, reflecting different construction methods and fire safety requirements. It should be noted that wood and wood surrogate, as well as concrete and concrete surrogate, may appear as separate material categories depending on their source and application. For instance, pure timber used in flooring or fibreboard is classified as wood, while cast concrete or slate is categorized as concrete. By contrast, surrogate classes are typically used for structural elements such as basements, roof beams or columns, where they serve as proxy categories representing broader groups of concrete- or wood-derived materials (Amini et al. 2024). In some cases, however, these surrogates can be further disaggregated into the core categories of wood and concrete. Other materials including glass, steel, insulation, cement, paper and cardboard collectively account for around 10–20% of the total material mass (Amini et al. 2024).

These findings are crucial not only for accurate analysis but also for developing a broader understanding of the national context, particularly the prevailing building trends and construction methods, and how these can inform and support circular economy strategies.

2.3 Material stock analysis in the built environment

Material stock analysis (MSA) corresponds to tracking the material composition, quantity and location of these materials (Mohammadiziazi and Bilec 2022), and it is critical for evaluation of energy use, material stocks and flows and the associated environmental performance across the life cycle of building stocks within a defined system (like a city or building) (Pei et al. 2024). MSA has become an essential approach in understanding the environmental impacts of the built environment. In particular, it helps link in-use material stocks with embodied GHG emissions resulting from their production, as well as estimate associated impacts on biodiversity and other environmental factors.

2.3.1 Methods and scales used in material stock analysis

Global assessments of material stocks have mostly treated human-made structures as a single category, without distinguishing between end-uses or structure types, leaving the specific share of buildings uncertain. Most studies have focused on global or regional scales and lack national or sub-national level detail. Recent works of Krausmann et al. (2017) and Wiedenhofer et al. (2021) estimated material stocks using material flow and lifetime data and Plank et al. (2022) moved toward distinguishing stock categories and end-uses such as buildings, roads and civil engineering. Some studies of Gontia et al. (2020), Noll et al. (2022) and Tanikawa et al. (2021) quantified building mass at city, regional or national scales, but few extended to broader levels. For example, Marinova et al. (2020) estimated global residential building stocks, while Pauliuk et al. (2021); Pauliuk (2024) modelled cement and metal in residential buildings, but these studies lacked spatial explicitness and comprehensive material coverage. Spatially resolved mapping is important because built environment patterns influence resource use (Haberl et al. 2023) and indicate secondary resource potentials (Haberl et al. 2021).

Various methods and modelling approaches have been developed to quantify material stocks, flows and compositions across different spatial and temporal scales. These methods may take either dynamic or static approach and adopt either retrospective or prospective perspectives (Brunner and Rechberger 2016). Temporal analysis help evaluate both historical developments and potential future trends, while spatial analysis captures the geographical distribution of materials across different regions. All of these aspects are crucial for effective resource management (Tanikawa and Hashimoto 2009).

Methods to achieve spatially explicit mapping include nighttime lights (Peled and Fishman 2021), cadastral data (Lanau and Liu 2020), big-data approaches (Mao et al. 2020) and LiDAR (Light Detection and Ranging) technologies (Schandl et al. 2020). However, these methods often struggle to separate buildings from other structures like roads or to differentiate building types, and they face challenges such as data saturation or limited spatial coverage. Since cadastral datasets and LiDAR are typically restricted to small areas, achieving consistent wall-to-wall mapping remains challenging. Recent advances suggest combining multispectral satellite Earth Observation data to identify buildings with crowd-sourced datasets such as OSM for roads, as demonstrated in Germany and Austria (Haberl et al. 2021).

Among the most widely used methods to quantify materials is Material Flow Analysis (MFA), which assesses the state and dynamics of material stocks and flows within a system defined by specific spatial and temporal boundaries (Brunner and Rechberger 2016). When combined with geospatial tools such as Geographic Information Systems (GIS), MFA allows analysts to associate material quantities with specific locations (Baccini and Brunner 2012). This spatial integration is particularly valuable for planning future resource needs, forecasting waste generation and implementing circular economy strategies.

Temporal perspectives are equally important: ageing building stocks such as those constructed during last century are expected to generate significant waste flows in the near future. To effectively assess urban metabolism in relation to buildings and infrastructure, it is also essential to understand changes in material accumulation temporally. Combining spatial and temporal approaches, the dual perspective enables a better anticipation of future resource needs and waste generation, supporting more informed planning and circular economy strategies. This spatial integration is crucial for efficient resource planning and use and for understanding the geographic distribution of human activities and built infrastructure (Tanikawa and Hashimoto 2009).

2.3.2 Material stock analysis in Norwegian context

Estimating material stocks in the built environment has been the focus of numerous studies, conducted across various geographical scales (from local to global) and over different temporal ranges, from single-year snapshots to century-long analyses (Augiseau and Barles 2017). However, there are a few studies that have focused specifically on quantifying material stocks in Norwegian buildings (Amini et al. 2024).

Bergsdal et al. (2007) applied MFA to assess stocks and flows of two primary construction materials (wood and concrete) based on projected demand for floor area at national scale in Norway. Subsequent research by Lausselet et al. (2020) examined embodied emissions and life cycle assessment (LCA) of buildings, primarily through detailed case studies of single-family houses at a neighbourhood level. Wiik et al. (2020) gathered 130 case-study buildings with various types and showed the dominance of foundation, external walls and supporting structure as contributors to their embodied emissions.

Although these studies have provided valuable insights, there were no attempts of doing a spatially explicit analysis of the Norwegian material stock at municipal level. Understanding the amounts and geographical distribution of materials across the country could be highly beneficial, supporting more accurate emissions assessments, better resource management and the development of targeted circular economy strategies.

2.4 LCA principles and application

Life-cycle assessment (LCA) is a standardized method (*ISO 14040:* 2006; *ISO 14044:* 2006) commonly used to estimate how potential environmental impacts accumulate across the different phases and components of a system's life cycle (Hellweg and Milà i Canals 2014). LCA has become increasingly applied to assess the environmental performance of buildings and neighbourhoods, and it is the preferred method for quantifying both direct and embodied GHG emissions associated with buildings. This includes emissions from raw material extraction, material production, transportation, operation and eventual decommissioning over the building's lifetime (Resch et al. 2020). For building-specific assessments, the European standard EN 15978:2011 (iTeh Standards 2011) provides a structured methodology aligned with the ISO framework, defining clear life cycle stages tailored to construction works.

2.4.1 LCA stages

LCA typically consists of four steps or stages. The first phase involves the definition of the goal and scope, where the purpose of the study is established and system boundaries are set. In the context of residential buildings, the objective might be to quantify the environmental impacts associated with the entire building life cycle. This includes resource extraction, the production of materials used in construction, transportation to the building site, operational use and end-of-life processes such as demolition and disposal (Hellweg and Milà i Canals 2014).

The second phase is the inventory analysis, in which all relevant inputs (such as energy and raw materials) and outputs (such as emissions and waste) are collected for each process in the building's life cycle (Hellweg and Milà i Canals 2014). For buildings, this can include hundreds of different emission flows and resource consumptions, compiled and aggregated across the entire system.

In the third phase, life-cycle impact assessment, the inventory data is categorized into environmental impact indicators and translated into comparable metrics. For example, both carbon dioxide and methane emissions can be expressed in terms of CO_2e using the Global Warming Potentials (GWP) (Fuglestvedt et al. 2003). This makes it possible to evaluate the climate change potential (commonly referred to as the carbon footprint) of different materials or building components (Hellweg and Milà i Canals 2014).

The final phase is the interpretation of results, where findings from the inventory and impact assessment are analyzed to answer the original objectives of the study (Resch et al. 2020).

2.4.2 LCA application and challenges in building sector

Many LCAs have been conducted within the building sector by urban planners, property developers, architects, engineers and consultants. Environmental Product Declarations have become an effective means of communicating the environmental performance of materials and semi-finished products. In addition to product-level assessments, existing studies also evaluate whole building systems, accounting for all life-cycle stages and, in some cases, even entire urban settlements (Hellweg and Milà i Canals 2014).

However, LCA results can carry significant uncertainties due to the large volume of measured and simulated data, as well as the simplified representation of complex environmental cause-effect relationships (Hellweg and Milà i Canals 2014), especially in the field of residential buildings. In this study, such uncertainties are particularly relevant when estimating embodied emissions from material production and manufacturing across a wide geographical scope, such as Norwegian municipalities.

Additionally, carbon accounting can be performed using different approaches, most commonly territorial-based and consumption-based methods. The territorial approach counts emissions that occur within a country or region during the production of goods and services. In contrast, the consumption-based method attributes emissions to the goods and services consumed within a territorial unit, regardless of where those emissions physically occurred. This distinction is important, as consumption-based accounting requires decoupling emissions not only from domestic industrial production but also from the global supply chains supporting local consumption and lifestyles (Tukker et al. 2020). In the context of material consumption and use, this approach can introduce higher uncertainty due to limited data on the origin of materials, making it more difficult to track emissions accurately across international boundaries.

In addition to it, acquiring reliable spatial data on building materials remains a considerable challenge. Data gaps, particularly in the availability of complete product inventories and construction-specific details, limit the precision of emissions estimates (Hellweg and Milà i Canals 2014). In the future, more standardized and spatially resolved data on material use in buildings could support the development of environmental profiles, which may offer more targeted insights and help identify emission hotspots related to material consumption patterns across different regions.

2.5 Frameworks for visualizing and communicating complex data

2.5.1 Data science frameworks

Data science has emerged as a rapidly developing field that requires a multidisciplinary approach and is closely linked to Big Data and data-driven technologies, which have had a transformational impact across research and industry domains (Demchenko et al. 2016). Much of the conceptual foundation of data science stems from a data-centric perspective. For instance, data-driven science is often interpreted through the lens of open data reuse (*OECD Principles and Guidelines for Access to Research Data from Public Funding* 2007). The establishment of data science as an academic discipline has been the subject of intensive debate within the research community (Smith 2015). Rather than being limited to data analysis, the field encompasses a broader body of knowledge that spans computing, communication and decision-making. As such, data science has been described as a combination of statistics, mathematics, computer science, graphic design, data mining, human–computer interaction and information visualization (Cao 2018).

Unlike the trajectory of Big Data, which has been primarily driven by business and private enterprise, researchers and scientists have also played a central role in shaping the data science agenda. From its origins in the statistics community, the field has expanded into multiple disciplines, promoting its development as a research area. A defining characteristic of this shift has been the strong embrace of the open model. This model enables free, distributed and collaborative approaches across society, economy, and research, standing in contrast to earlier closed frameworks (Cao 2018).

The rise of open data initiatives reflects this transition. National and regional programs have been introduced in the United States ("US Government Open Data" 2025), the United Kingdom ("UK Open Data" 2025) and the European Union ("The European Union Open Data Portal" 2025). Alongside these, the academic sphere has increasingly supported Open Access publishing, while diverse scientific communities have created sharable repositories, for example, global climate data (S.L 2025) and the UCI Machine Learning Repository ("UCI Machine Learning Repository" 2025).

To sum it up, data science has evolved into a multidisciplinary field shaped by the open data movement, technological advances, providing a robust foundation for research, innovation and practical applications in multiple disciplines including urban and environmental sciences.

2.5.2 Role of interactive visualization in environmental and urban disciplines

Contemporary environmental and urban planning processes involve a wide range of stakeholders, which creates the need for dialogue tools that can facilitate communication across disciplinary boundaries (Billger et al. 2017). Technological developments, particularly advances in visualization tools, present both opportunities and challenges for participatory planning. A variety of visualization platforms are continuously being developed within and outside academia, spanning multiple disciplines. In the case of 2D platforms, typical functions include the collection and sharing of location-based information, often allowing users to contribute experiential data and engage in discussions about specific places. Examples of such features include placing markers on a map or generating images (Billger et al. 2017). In addition, more advanced applications extend beyond visible aspects of the built environment to include simulated development scenarios (Brömmelstroet 2013; Pelzer and Geertman 2013) or multi-criteria evaluations used to analyze and compare planning alternatives (Ban et al., n.d.).

Understanding the purpose of these tools requires considering the intentions of their developers and the audiences for which they are designed. While organizational affiliations of researchers are usually clear through their publications, their disciplinary backgrounds are less transparent. What is relevant in this context is whether a tool is created for use primarily by other researchers, whether it is developed for prospective users and tested in practice, or whether the objective is full implementation. Within this landscape, several categories of collaboration in tool development can be distinguished, among those are: researchers developing tools for other researchers, researchers creating tools for decision makers or stakeholders in urban planning, and joint collaborations between researchers, developers, and planning professionals (Billger et al. 2017).

In summary, visualization tools represent a rapidly evolving field at the intersection of research, technology, and practice. Their potential lies not only in supporting communication among diverse stakeholders, but also in providing replicable frameworks that can inform decision-making in environmental and urban planning contexts.

2.5.3 Key metrics for dashboard communication

Data dashboards are visual displays that consolidate key information needed to achieve specific goals on a single screen. They are increasingly common in communication and research, where they function as monitoring tools designed to be understood at a glance. As with any tool, however, it is important to consider when dashboards are appropriate. Their primary role is to present quantitative measures of outputs and outcomes, often with comparative elements, in order to monitor progress toward defined objectives. Dashboards intended for analytical purposes are typically used by policymakers, researchers and others. To be effective, they should be interactive, allowing users to drill down into details and to explore and examine the data by various types of maps, plots and graphs. Once the appropriate type of graph or visualization is selected, it must also be carefully designed to match the specific measure being represented (Smith 2013).

In addition to it, the integration of dashboards with geospatial technologies has opened further opportunities for visualisation and decision-making. Geographic concepts and perspectives can be communicated more effectively and engagingly through web mapping tools and spatial data, enabled by geographic information (GIS) systems (Kerski 2020). Therefore, map-based dashboard tools have emerged as particularly valuable for visualizing and understanding large volumes of geo-referenced data and their complex relationships. In the case where maps are used in a dashboard tool for visualisation, a typical interface may include the following panels: the title panel, the toolbar panel, the spatial panel, the temporal panel and the ranking panel. Also, eye-tracking studies and user interviews have demonstrated that map-based dashboards can effectively support spatiotemporal knowledge acquisition, while also highlighting design limitations and opportunities for improvement (Zuo et al. 2020).

In sum, dashboards, particularly when integrated with GIS and map-based interfaces, offer powerful means of communicating complex data in accessible and interactive formats. While their effectiveness depends on thoughtful design and appropriate application, they hold strong potential for supporting decision-making in diverse contexts.

3. Methodology

3.1 Modelling material stocks in residential buildings

Mapping material stocks in buildings plays an important role in understanding resource use and environmental impacts within the built environment. This section focuses on quantifying and mapping material stocks in Norwegian residential buildings as well as assessing the embodied carbon footprint resulting from material production and buildings manufacturing at the municipality level. This process includes linking statistical building data to physical material intensities, classifying building archetypes, assessing embodied carbon emissions and scaling the data spatially. Different methodological steps were followed to ensure that the results are representative, reproducible and adaptable to future work.

3.1.1 Case study

The residential housing stock of Norway at the municipality level was chosen as a case study to test the proposed methodology. This country and scope were chosen due to its robust statistics system, open access to detailed spatial data and its commitment to sustainability in the building sector (Wiik 2023).

Norway is located in the northern part of Europe and divided into 15 counties and 357 municipalities (“NUTS – Eurostat” 2025). As of June 2025, the country has a population of over 5.5 million inhabitants, unevenly distributed across municipalities, with the highest population concentrations found in and around the capital city Oslo, as well as around Bergen and Trondheim (SSB Population 2025).

Residential buildings across the country form a significant proportion of the total building stock. According to Statistics Norway, residential buildings number 1,604,505 in 2025, accounting for approximately 36% of the total building stock in the country (4,343,042 buildings) (SSB Building Stock 2025). For an efficient and more structured analysis, the residential stock was further classified by building type and construction period. This study adopts the typology which categorizes buildings into three types: single-family houses (SFH), multi-family houses (MFH) and apartment blocks (AB), as well as includes eight construction cohorts ranging from 1955 to 2024 (Amini et al. 2024; Pauliuk 2024; Sandberg et al. 2016; 2017).

Due to Norway’s geographic, climatic and historical context, certain construction materials dominate the residential building stock. These include cement, concrete, steel, glass, wood, insulation materials (primarily mineral wool (“722.506 Post-Insulation of Floor Partitions above Basements and Crawl Spaces - Building Research Series” 2004),(“723.511 Post-Insulation of Wooden Exterior Walls - Building Research Series” 2023)), and paper and cardboard. The proportion of each material varies by building type and cohort, reflecting changes in construction practices, regulatory standards and material availability (Amini et al. 2024).

Although the methodology is applied to Norway in this study, its modular structure allows for adaptation to other countries or regions with similar or better data availability. The diversity of Norway’s building stock and the availability of disaggregated municipal-level data make it a suitable test case for broader methodological implementation.

3.1.2 Data sources

Most of the datasets used in this study were obtained from Statistics Norway (SSB, 2025), published papers (Sandberg et al. 2016; Amini et al. 2024), and the ODYM-RECC database (Pauliuk 2024; Pauliuk et al. 2021). Georeferenced data for mapping, visualization and dashboard development were sourced from GeoNorge (*Norske Fylker Og Kommuner - Kartkatalogen* 2024) and SSB Kart (SSB Kart 2025). The specific datasets used, along with additional details, are described in the following chapters.

3.1.3 Stock composition

To assess material stocks in Norway at the municipal level, data from different sources were gathered and combined. There are several ways this type of analysis can be done, but in this study, it was carried out by combining three main components: the number of dwellings for each archetype present in Norwegian municipalities, material inventories per archetype and average heated floor area per building.

One of the primary data sources used in this study is Statistics Norway (SSB, 2025), which provides a wide range of datasets related to the Norwegian building stock. Relevant information includes building types, year of construction and distribution across Norwegian municipalities. Specifically, Table 06266: Dwellings, by type of building and year of construction (M) 2006–2024 (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025) was utilized to obtain detailed data on the residential building stock. In addition, Table 03175: Existing building stocks. Residential buildings, by type of building (M) 2001–2025 (SSB 03175: Existing Building Stocks 2025) from Statistics Norway was initially used during the early stages of the analysis to support some intermediate steps. However, it was later excluded from the final analysis due to its limited relevance or consistency with the main dataset.

Data from Table 06266 from Statistics Norway (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025) was obtained directly from the platform by applying the following filters: under the 'Contents' field, ‘Dwellings’ was selected; the year was set to 2024; all municipalities were included under 'Region'; all options under 'Type of building' were selected except ‘Other’; and all options from 'Year of construction of the building' ranging from ' 1900 and earlier' to '2021 and after' and ‘Unknown’ were included. The ‘Other’ types of dwellings were analyzed and estimated separately; a more detailed description is provided in the following chapter of this work. Once the table with the specified parameters was generated, it was manually pivoted four times clockwise until the municipalities appeared in the rows, and 'Type of building' and 'Year of construction of the building' were in the columns. This dataset format was selected because it most closely follows the principles of the first normal form (1NF), allowing for more efficient data manipulation and wrangling during the analysis process. The resulting table was then downloaded in Excel (XLSX) format.

For Table 03175 (SSB 03175: Existing Building Stocks 2025) ‘Existing buildings’ were chosen under ‘Contents’, the year was also set to 2024, all municipalities were included under ‘Region’. All building types were selected under ‘Type of building’. As the dataset contained a relatively limited number of entries and was already in a suitable format, no pivoting was required, and it was exported directly in Excel (XLSX) format.

3.1.4 Residential building archetypes

Material inventories and heated floor area for each archetype were taken from literature sources and used to estimate the amount of materials embedded in buildings. Inventories of different material types and average heated floor area per building archetype were obtained from a study by Amini et al. (2024), which provides average estimates of material quantities used in the construction of representative residential buildings in Norway. The material inventory dataset included the following material types, disaggregated by building type and construction cohort: cement, concrete, concrete surrogate, construction-grade steel, glass, insulation, wood and wood products, wood surrogate, paper and cardboard, and a category labeled ‘other’, which encompassed a mix of metals, gypsum and bitumen. Additionally, a ‘TOTAL’ category representing the sum of all materials per type and cohort was included. When reviewing the raw data on material inventories, the quantities associated with the ‘other’ material category were consistently minimal, typically amounting to just around one kilogram per building. In contrast, total material inventories per building reached hundreds of tonnes for SFH and MFH, and thousands of tonnes for AB. As a result, the ‘other’ category accounted for only approximately 0.00001% to 0.0001% of the total mass. Therefore, the ‘other’ category was excluded from further analysis due to its negligible contribution to the overall stock and the lack of specificity required for material-level emissions analysis in subsequent stages. The tables on material inventories and average area per building archetype were extracted directly from the supplementary materials of the scientific paper and saved as separate CSV files to ensure good data management practices.

Another key data source was Sandberg et al. (2017), which provides a table B.1 ‘Cohort definition and average heated floor area per dwelling in each segment’. This table includes estimates of average heated floor area for various defined building archetypes and was essential for linking archetypes to material composition and stock modelling. Table B.1 (Sandberg et al. 2017), containing cohort definitions and the average heated floor area per dwelling in each segment, was manually recreated in Excel format. As the table was originally available in the PDF format within the Supplementary of the journal article, it was necessary to convert it into the format compatible with data analysis. For consistency, the ‘Start year’ and ‘End year’ rows representing the time period of building construction in the original table were merged into a single row with both years joined by an underscore.

3.1.5 Mapping material stocks

All tabular datasets were exported to a Jupyter Notebook environment (Version 7.1.0) running on Python 3 (ipykernel). Using the ‘pandas’ library, the data was cleaned and standardized into third normal form (3NF). Rows with missing values were removed, and column names were modified to replace spaces and dashes with underscores for consistency.

To ensure interoperability across datasets, particularly in preparation for merging, building archetype column labels were harmonized into the following standard categories: single-family house (SFH), multi-family house (MFH) and apartment block (AB). These were further segmented by construction year into the following groups based on Amini et al. (2024) developed to fit ODYM-RECC (Pauliuk 2024): 1955, 1956–1970, 1971–1980, 1981–1990, 1991–2000, 2001–2010, 2011–2020 and 2021 with dashes replaced by underscores as mentioned above.

The building categories provided in Statistics Norway Table 06266 (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025) differed from the mentioned classification scheme used in this study; therefore, a reclassification as stated in Table 1 according to ODYM-RECC database (Pauliuk et al. 2021; Pauliuk 2024) was carried out to ensure consistency with the defined archetypes. As part of the data pre-processing, it was necessary to examine the category ‘Other’ in the dwelling types listed in Table 06266 from Statistics Norway (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025). This category was assessed to determine whether these dwellings align more closely with existing archetypes (SFH, MFH or AB) based on number of dwellings of certain archetype per capita at municipal level. The analysis helped to estimate which archetype the ‘Other’ category is most similar to in different municipalities and guided the decision on whether to include or exclude this category in further calculations. The results of this analysis, along with the reasoning for the final decision, are presented in the Results chapter of this work.

Table 1 – Overview of SSB and ODYM-RECC types

SSB type	**ODYM-RECC type**
Detached house	SFH
House with 2 dwellings	MFH
Row house, linked house and house with 3 dwellings or more	
Multi-dwelling building	AB
Residence for communities	
Other buildings	Excluded

Construction years (cohorts) were also harmonized according to Table 1 based on the ODYM-RECC database (Pauliuk et al. 2021; Pauliuk 2024).

Table 2 – Overview of SSB and ODYM-RECC cohorts

SSB cohort	ODYM-RECC cohort
1900 and earlier	Before 1955
1901-1920	
1921-1940	
1941-1945	
1946-1960	
1961-1970	1956-1970
1971-1980	1971-1980
1981-1990	1981-1990
1991-2000	1991-2000
2001-2010	2001-2010
2011-2020	2011-2020
2021 and after	After 2021
Unknown	Excluded

In addition, three municipalities present in Table 06266 (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025) were excluded from the analysis: ‘K-21-22 Svalbard and Jan Mayen’, ‘K-23 Continental shelf’ and ‘K-Rest Divided municipalities and unknown’. Svalbard and Jan Mayen are two remote island territories which are commonly grouped separately for administrative and statistical purposes. Norway’s continental shelf areas are parts of the seabed and are not municipalities in the traditional sense. Divided municipalities are areas that may be split across multiple statistical or territorial units for some reason. In addition to it, these tree municipalities were not included in the raw municipality masks dataset from Maps from Statistics Norway (SSB Kart 2025), and it was impossible to use them for the comprehensive analysis.

Table B.1 (Sandberg et al. 2017) was also reclassified for consistency to allow merging the datasets based on common fields. Since a different classification method was used to define archetypes in this study, MFH were grouped under AB and Terraced houses (TH) were renamed to MFH aligning with the archetype scheme (Lausselet et al. 2020) used in this work. Cohorts spanning 1800–1955 were grouped under ‘1955’, and those spanning 2021–2050 were changed to ‘2021’.

Geospatial data was processed primarily using QGIS-LTR software (Long-Term Release 3.28), with all shapefiles projected to EPSG: 32633 to ensure spatial consistency.

The assessment of material stocks can be performed using various methods and approaches. In this study, two different methods were applied to address the key challenge of data inconsistency, namely, the fact that Table 06266 (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025) provides data on the number of dwellings, whereas material inventory data is available at the building level.

To handle this mismatch, the first method focusing on estimating the average number of dwellings per building for each archetype, enabled the conversion of dwelling-level data into building-level estimates. To implement this, raw data were extracted from Statistics Norway Tables 06266 (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025) (number of dwellings) and 03175 (SSB 03175: Existing Building Stocks 2025) (number of residential buildings) for the year 2024. The total number of dwellings per building type was obtained by summing the respective values in Table 06266 (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025), and this sum was then divided by the number of buildings from Table 03175 (SSB 03175: Existing Building Stocks 2025), showing the average number of dwellings per building by building type. These averages were subsequently used to recalculate the number of dwellings per building across all detailed archetypes, including variations by construction year and municipalities. With the updated number of buildings estimated from dwelling data, total material stocks per municipality were then calculated by applying the material intensity data through simple multiplication. However, due to a number of assumptions, this approach was not used for the final material stock calculations.

The second approach of the assessment of material stocks was carried out by first estimating the total heated floor area per building archetype across Norwegian municipalities. This was done by using data from Table 06266 (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025), which provides the number of dwellings by building type and construction year. These values were multiplied by the average heated floor area per dwelling from Table B.1 (Sandberg et al. 2017) which offers archetype-specific estimates. This approach enabled the calculation of total heated floor area per archetype and municipality using the following equation (1):

$$\mathrm{S}_{\mathrm{total,j}} = \mathrm{N} \times \mathrm{S}_{\mathrm{av,j}} \tag{1}$$

Where:

$S_{total,j}$ – Total heated floor area of archetype j in the municipality [m²];

N – Number of dwellings;

$S_{av,j}$ – Average heated floor area per dwelling of archetype j [m²].

To calculate material stocks, material intensities in kilograms per square meter (kg/m²) were derived from the datasets containing material inventories (kg) and corresponding average area (m²) per building archetype (Amini et al. 2024). Since the data for the most recent cohort (2021 and later) was not included in the original datasets, it was assumed that the characteristics of the '2011–2020' cohort would sufficiently represent the most recent cohort. Therefore, the corresponding values were duplicated for consistency. The table containing material inventories provides total material mass per building, which was divided by the archetype-specific average heated floor area per building to get material intensity values per square meter, using to the following equation (2):

$$\mathrm{M}_{\mathrm{int,i,j}} = \frac{\mathrm{MI}_{\mathrm{i,j}}}{\mathrm{S}_{\mathrm{av,j}}} \tag{2}$$

Where:

$M_{int,I,j}$ – Material intensity of material type i per building of archetype j [kg/m²];

$MI_{i,j}$ – Material inventory of material type i per building of archetype j [kg];

$S_{av,j}$ – Average heated floor area per building of archetype j [m²].

Finally, the total heated floor area per archetype in each municipality was multiplied by the corresponding material intensity (kg/m²) to estimate total material stocks per material type and archetype at the municipal level according to the following equation (3):

$$\mathrm{A}_{\mathrm{i,j}} = \mathrm{S}_{\mathrm{total,j}} \times \mathrm{M}_{\mathrm{int,i,j}} \tag{3}$$

Where:

$A_{i,j}$ – Total material stock of material type i per archetype j [kg];

$S_{total,j}$ – Total heated floor area of archetype j in the municipality [m²];

$M_{int,I,j}$ – Material intensity of material type i per building of archetype j $[\mathrm{kg/m^2}]$.

Georeferenced data on Norwegian municipalities including municipal codes ('kommunenummer', in Norwegian), official names ('kommunenavn', in Norwegian), and geographic boundaries was obtained from Maps from Statistics Norway (SSB Kart 2025), enabling more detailed material stock mapping and clearer, more visually effective representations. These spatial data were available in multiple formats, including shapefiles and CSV tables, and were used for mapping and municipal analysis. For the municipality masks, the 'Manage layers and categories' section was used to select the 'Administrative borders 2024' category and the 'Municipalities 2024' subcategory, which were then exported as a SHP file (EPSG: 32633). In addition to that, the 2024 municipality and county boundary maps, showing the coastline and excluding water areas, were downloaded in the GeoPackage format to accurately represent the country's borders (*Norske Fylker Og Kommuner - Kartkatalogen* 2024).

3.1.6 Embodied emissions in residential buildings

Based on the calculated material stock totals and total heated floor area at the municipal level in Norway, it was possible to estimate the embodied environmental impacts using several approaches, including greenhouse gas (GHG) emissions, biodiversity loss and human health effects. This allowed for a more comprehensive understanding of the environmental footprint of the built environment.

Data on embodied GHG emissions were obtained from the ODYM-RECC database, a comprehensive resource containing detailed emission data across material production and manufacturing processes. For this work, the following datasets were used: 4_EI_ManufacturingEnergyIntensity_V2.2 table, 6_PR_DirectEmissions_V1.2 table and 24_PE_ProcessExtensions_Materials_VN1.0 table. These datasets provided emission intensity values required for assessing the environmental impacts associated with different material flows in the building sector. Data from the ODYM-RECC database (Pauliuk et al. 2021; Pauliuk 2024) was accessed via the Zenodo platform and downloaded as a ZIP file (RECC_v2.5_GlobalBuildings.zip).

For estimating emissions related to the manufacturing of SFH, MFH and AB buildings, the energy intensity values (in MJ/m²) were multiplied by the total heated floor area (in m²) per municipality. These energy demands were then allocated across different energy carriers available in the dataset 4_EI_ManufacturingEnergyIntensity_V2.2 (electricity, diesel, natural gas and gasoline) using the equation (4):

$$\mathrm{E_{j,k}} = \mathrm{E_{int,j,k}} \times \mathrm{S_{total,j}} \tag{4}$$

Where:

$E_{j,k}$ – Total energy demand for manufacturing the heated floor area of archetype j using energy carrier k [MJ];

$E_{int,j,k}$ – Energy intensity of manufacturing per unit area of archetype j using energy carrier k [MJ/m²];

$S_{total,j}$ – Total heated floor area of archetype j in the municipality [m²].

To estimate direct CO_2 emissions, each energy carrier's corresponding Carbon Intensity (kg CO_2e/MJ) available in 6_PR_DirectEmissions_V1.2 from ODYM-RECC (Pauliuk et al. 2021; Pauliuk 2024) was applied to the energy demands using the equation (5):

$$D_k = E_k \times F_k \tag{5}$$

Where:

D_k – Direct CO_2e emissions resulting from the use of energy carrier k [kg CO_2e];

E_k – Energy demand associated with energy carrier k [MJ];

F_k – Carbon intensity (CI) for energy carrier k, representing direct CO_2 emissions per unit of energy [kg CO_2e/MJ].

Since emission data for electricity was not included in the6_PR_DirectEmissions_V1.2 dataset, a Norwegian electricity mix value of 30 g CO_2e/kWh (Scarlat et al. 2022) was used instead, which was converted into kg CO_2e /MJ units to ensure consistency across calculations.

For the second part of the analysis, direct emissions from the production of individual material types were calculated. For that, the total mass of different material types per municipality were multiplied by the corresponding 100-year horizon Global Warming Potential values (GWP100) provided in 4_PE_ProcessExtensions_Materials_VN1.0 dataset from ODYM-RECC database (Pauliuk et al. 2021; Pauliuk 2024).

$$D_{\mathrm{i}} = GWP_{\mathrm{i}} \times \mathrm{M_i} \tag{6}$$

Where:

D_i – CO_2 emissions resulting from the production of a material type i [kg CO_2e]

GWP_i – Global Warming Potential 100 (GWP100) [kg CO_2e/kg];

M_i – total mass of material type i in the municipality [kg].

The final emissions were converted from kilograms to megatons (Mt) for simplification.

3.1.7 Uncertainty analysis

Since the data provided by the referenced sources consisted of single point estimates without associated variability ranges, it was necessary to conduct an uncertainty analysis to define plausible intervals within which the values could vary. This step was essential not only to reflect potential data uncertainty but also to ensure that the methodology can be adapted and scaled for future research and implementation in other contexts or countries, where such variability ranges may be more readily available.

Monte Carlo simulation was selected as a suitable method for assessing propagation of uncertainty linked to variability in important parameters in this study. To implement this approach, it is necessary to assume an underlying probability distribution for the input data, such as a normal or triangular distribution (von Brömssen and Röös 2020). To avoid giving a false sense of certainty, distribution functions that follow the maximum entropy principle (Mishra and Datta-Gupta 2018; van der Spek et al. 2020) were chosen. For this reason, triangular distributions were used to set up probability density functions, as they work well when minimum, maximum and mode values are known for the parameters (Næss et al. 2025). The values provided in the original datasets were used as mode (most likely) values for the simulation, while the minimum and maximum values, which are also required for defining a triangular distribution, were defined based on the type and characteristics of the simulated data. For example, all data related to the oldest cohort (1955) was assigned a standard deviation of 30% to reflect the naturally higher uncertainty associated with older data. For the 1956-1970 cohort, a 20% range was applied. In contrast, the more recent cohorts were assumed to have lower uncertainty - 10%, based on expert opinion and better data availability. Regarding energy and carbon intensity data, efforts were made to source reliable values from credible literature. However, due to the geographically specific nature of this study, it was not feasible to apply global averages or generalized values found in the literature as they do not reflect Norwegian conditions. Despite the relatively high level of uncertainty associated with the assumptions used for the Monte Carlo simulation parameters, the analysis was primarily conducted to explore the propagation of uncertainty from parameter variability and for visualisation purposes. The detailed parameters and values used in the Monte Carlo simulation process are provided in Table A1 provided in Annex part of this document.

While the Heated Floor Area (HFA) values per dwelling type and cohort, carbon intensities (CI) or emission factors for specific energy carriers, and GWP100 values were simulated independently, the simulations involving material inventories (MI) and manufacturing energy intensities (EI) per m² followed a different procedure. This was due to the structure of the original datasets, which provided relative shares of materials required for constructing a single building and of energy carriers required for manufacturing 1 m² of a building. To maintain consistency and realism in the simulated data, it was essential to preserve these shares across all simulation runs. Therefore, before running Monte Carlo simulations, original shares of materials and energy carriers were calculated. Simulations were then applied to total intensities, and the shares were used to disaggregate results. This ensured realistic outcomes and avoided improbable distributions of materials or energy sources.

The data on dwellings per type and construction year available in Table 06266 (SSB 06266: Dwellings, by Type of Building and Year of Construction 2025) was considered sufficiently reliable; therefore, no uncertainty simulations were performed on it. After the Monte Carlo simulations were conducted for other datasets where uncertainty was more evident (material inventory per building (Amini et al. 2024), average heated floor area per dwelling (Sandberg et al. 2017) and data provided by ODYM-RECC (Pauliuk et al. 2021; Pauliuk 2024) which was necessary to assess embodied carbon emissions), full analysis was repeated by following the same procedures as outlined in Sections 3.2 Modelling of material stocks in residential buildings and 3.3 Embodied environmental impacts assessment, now incorporating the uncertainty ranges into the results. To ensure the efficiency of the process, all simulated datasets were stored using NumPy arrays and pandas DataFrames, maintaining consistent data structures. During the steps involving multiplication of values from various datasets, operations were performed by aligning and multiplying values with matching indices across the arrays and DataFrames. After all simulations were completed, key statistical metrics including the mean, maximum, minimum, standard deviation (in both absolute terms and as percentages), as well as the 5th and 95th percentiles were calculated and retained for visualization purposes. For example, mean values were used to visualize the average material stock and emissions across municipalities, forming the basis for general trend or 'real-life scenario' analysis. In contrast, minimum and maximum values represented the 'best-case' and 'worst-case' scenarios, respectively, providing a range that reflects the uncertainty and variability inherent in material stock and emission estimates. Additionally, the mean values for material stocks and embodied emissions were also spatially visualized using georeferenced data at municipal level and used for comparison against previous studies – material stock mean values were compared with the published ones (Rousseau et al. 2025) to validate the reliability of the current analysis; the results of the embodied GHG emissions were compared to another study (Lausselet et al. 2020). The structure of all datasets and comparative plots is presented in the Results section to support the validation process. The results containing all mentioned variables were exported as a denormalized dataset to support the development of an interactive dashboard, which constituted a following part of the analysis.

3.1.8 Data normalization

The practical analysis part of this study adapted datasets structured in third normal form, wrangling and merging them based on the primary key 'kommunenum' (municipality code) and an archetype defined as a combination of type and cohort. This approach ensured smooth integration of all data throughout the analysis.

In addition to it, this study adopts an ontology-driven framework for the built environment, in alignment with established systematic building decomposition method (Kaltenegger et al. 2025) representing a system moving from broad system-level typologies to more detailed property-level attributes. The result dataset used includes several attributes, among which were material stock (in kilograms) and associated emissions (in kg CO_2e), systematically organized by building type, construction cohort, material type and municipality. The attribute "material" stores names of various material types and corresponds directly to the Material level in the ontology (e.g., cement, glass, insulation). Meanwhile, attributes related to material stock and emissions represent environmental indicators and can be mapped to the indicator level. The municipality field serves as s spatial filter, enabling the disaggregation of environmental indicators across geography. This approach reinforces the importance of incorporating property measures when identifying and categorizing building materials.

3.1.9 LCA

For this study, LCA is applied to understand the embodied GHG emissions of materials found in Norwegian residential buildings, as identified through archetype modelling, as well as emissions resulted from building manufacturing. Thus, the scope and goal are limited to life cycle modules A1-A3 (Product stage) and A5 (Construction process stage) as defined in EN 15978:2011 (iTeh Standards 2011). These boundaries help ensure consistency when comparing building types, material compositions and construction periods.

LCA is a complex and multidimensional analysis, therefore, not all its stages were conducted in this thesis. Instead, the study focused on selected life-cycle stages most relevant to the research objectives and data availability, particularly material production and operational energy use. The analysis specifically examined which material, building types and cohorts contribute most significantly to the carbon footprint of typical Norwegian residential buildings. These insights can support strategies for emission reduction, improved material efficiency and greater circularity in residential construction.

3.2 Exploratory statistical analysis

Output from Monte Carlo simulations were treated as statistical samples for both material stock and total embodied GHG emissions, which include emissions from material production and dwelling manufacturing at the municipal level. A selection of socio-economic and geographical indicators was included in the analysis, primarily based on data availability. Relevant indicators such as gross domestic product (GDP), education level and area of urban settlements were obtained from Statistics Norway (SSB, 2025), while municipal area and latitude were extracted from georeferenced data of Norwegian municipalities.

3.2.1 Data preparation

After all necessary data were downloaded and imported, they were processed and formatted to meet the requirements for statistical analysis. For instance, total material stock and total embodied GHG emissions were divided by the population at municipal level. GDP per inhabitant data, originally available at the county level (SSB Regional Accounts 2025), were disaggregated to the municipal level by allocating county values across all municipalities within each respective county. Education level data (SSB Educational Attainment of the Population 2025) were categorized into three groups: basic, secondary and higher education. The share of each category was calculated by dividing the number of individuals within each education level by the total number of educated individuals in the municipality. Municipal area and latitude were extracted from the georeferenced dataset of Norwegian municipalities previously used in this study, using appropriate spatial functions. Population density was computed by dividing the total population by the area of urban settlements (SSB 14216: Area and Population of Urban Settlements 2025) of the corresponding municipality.

Finally, all indicator values were merged into a single dataset using the municipality code ('kommunenum') as a key, forming the basis for the statistical analysis.

3.2.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was performed to reduce the dimensionality of the dataset and to explore the underlying structure among Norwegian municipalities based on socio-environmental and geographical indicators. The main objective of applying PCA in this context was to identify possible patterns and correlations among variables while minimizing information loss. The input indicators and corresponding units are described in Table 3.

Table 3 – Input data used for statistical analysis

Indicator	**Attribute in the dataset**	**Unit**
Total material stock per capita	material_stock_capita	kilogram/capita
Total emissions per capita	emissions_capita	CO_2e/capita
GDP per capita	gdp_capita	10000 NOK/capita
Basic school level share	basic_school_share	%
Secondary school level share	secondary_school_share	%
Higher school level share	high_school_share	%
Population density in urban settlements	population_density	persons/km² of urban settlement
Area	area_km2	km²
Latitude	lalitude	degree

To ensure comparability across indicators with differing units and magnitudes, all numerical variables were normalized. This standardization was a crucial step, as PCA is sensitive to the variance of the input variables and can be skewed if variables are on incompatible scales.

PCA was implemented using Python's scikit-learn library. The standardized dataset served as the input for the PCA function, which assessed the covariance matrix to identify directions of maximum variance in the data. No specific number of components was preselected, instead, the full set of principal components was initially examined to evaluate how much variance each component explained.

A plot was generated to visualize the cumulative variance explained by principal components. This visual aid supported the determination of an optimal number of components to retain, using the 'elbow criterion'. To interpret the meaning of the principal components, loadings (correlation between the original variables and the components) were examined. Each loading indicated how strongly a variable contributes to a component.

A biplot of municipalities projected onto the first two principal components was also created to interpret the possible correlations. Municipalities were represented as points, while variable loadings were represented as arrows. The direction and length of each arrow indicate the influence and contribution of a variable to the component space. Both the correlation matrix and the biplot, as well as their interpretation are described in the Results section of this work.

The Jupyter Notebooks containing scripts with the entire analysis is available in the GitHub repository [https://github.com/DolgayaMaria/material-stock-analysis], and the schema of the entire workflow (Figure A6) is available in the Annex of this work.

3.3 Dashboard for interactive communication

The dashboard serves as an interactive and effective tool for communicating results to support decision-making. In this study, it was used to visualize material stocks, emissions from material production and emissions from building manufacturing, enabling clear and accessible presentation of key findings and answering the research questions formulated in the beginning of the work.

3.3.1 Target audience and user's story

To effectively communicate the results, it is essential to clearly identify the intended target audience that the dashboard is designed to support in their decision-making processes. In this study, the primary audience consists of municipal advisers who require data to inform policy development, decision-making and policy implementation at the local level.

With this user group in mind, the entire layout and structure of the dashboard were designed to ensure intuitive interaction and relevance to practical decision-making. A key feature of the interface is a map of Norwegian municipalities, which visually conveys the geographical distribution of material stocks and associated emissions. This allows users to easily identify regions with high resource intensity or elevated embodied or manufacturing emissions – information that can directly support resource management and climate policy planning at the municipal scale.

A user story was developed to guide the interface design and ensure usability. For example, the map was intentionally placed on the left side of the dashboard, aligning with the natural left-to-right reading direction common in European cultures. This layout encourages users to begin with the visual summary (map with Norwegian municipalities) and then progress to more detailed insights presented in bar charts on the right. In addition to supporting visual navigation, the user story also shaped how data relationships are presented. Emissions from material production were directly linked to material stocks, helping users understand which materials contribute most to emissions, and in which municipalities these impacts are most significant. This integrated view allows for more informed, spatially specific policy considerations regarding both emission reduction and material efficiency strategies.

3.3.2 Tools used for building the dashboard

A combination of tools enabled the rapid development of a fully interactive, geographically aware dashboard that supports intuitive exploration of material stock and emissions data across Norway. The dashboard was built using the Python libraries Dash (Parmer Chris et al. 2025) and Plotly (Kruchten Nicolas et al. 2025). Dash, developed by Plotly, is a Python framework for creating web-based applications which allows for the seamless integration of interactive graphs, HTML components and user input elements within a reactive layout, making it particularly suitable for data visualization and exploratory analysis tasks. Plotly is used within Dash to generate interactive visualizations. It supports a broad range of chart types and provides built-in interactivity, such as zooming, hovering and selection callbacks that enhance user engagement. In this study, Plotly was used to create choropleth maps and bar charts, enabling users to explore both the geographic and categorical dimensions of the dataset.

Pandas (McKinney 2010; “Pandas-Dev/Pandas: Pandas” 2020) served as the foundation for data manipulation and preprocessing. It was used to filter, group and aggregate the dataset based on user interactions, such as selecting a municipality on the map or a material category in the chart. It also ensured data consistency and proper formatting, such as zero-padding municipality codes. To support geographic visualization, GeoPandas (Jordahl et al. 2020) was used for handling geospatial data in shapefile format. The shapefile of Norwegian municipalities was converted to GeoJSON, the format required by Plotly for map rendering. The geometries were reprojected to the WGS84 coordinate system (EPSG:4326) to ensure compatibility with web-based mapping tools.

Interactivity between visual components was managed using Dash callbacks. For example, when a user clicks on a map region or a chart bar, a callback function is triggered that filters the underlying data and updates the other visual elements accordingly. This dynamic functionality was essential for delivering a responsive and engaging user experience.

4. Results

4.1 Building and material stock assessment

4.1.1 ‘Other’ type of dwellings

The analysis of the ‘Other’ dwelling category suggested that based on the dwellings per capita ratios they generally resembled MFH or AB, with four cases where they were closer to SFH (Oslo, Bergen, Trondheim - Tråante and Bærum). Based on these findings, an attempt was made to redistribute ‘Other’ dwellings into the closest-fitting building types depending on the municipality. However, further analysis showed that the inclusion of ‘Other’ dwellings had only a minor effect on total material stock estimates across municipalities. To evaluate this, summary statistics were calculated, and results were aggregated by archetype, material type and municipality. The total material stock including ‘Other’ type of dwellings resulted in 264 Mt, whereas the total number for the stock excluding them was 258.5 Mt. Given that the changes in overall material quantities were not sufficient (2.21%), and that the reassignment of ‘Other’ dwellings relied on several assumptions without a strong confidence basis, the category was excluded from further analysis. The level of uncertainty introduced by including ‘Other’ was not justified by the limited impact it had on final results.

4.1.2 Main contributors to national material stock

When material stock assessment was performed, the dataset included the following attributes: type, cohort, kommunenum (municipality code), material, mean material stock, together with the minimum, maximum, 5th and 95th percentile and relative standard deviation (Table 4). The full dataset is available in the Zenodo repository as CSV file (Dolgaya et al. 2025).

Table 4 – The structure of the dataset containing statistical results on material stock at municipal level in Norway; ‘kommunenum’ (Norw.) refers to the municipal code

Attribute	**Description**
type	Type of dwelling, coded as AB (apartment block), MFH (multi-family house), SFH (single-family house)
cohort	Class of the periods of dwelling construction
kommunenum	Municipality code
material	Material type (cement, glass etc.)

material_stock_mean	Mean material stock in kilograms
material_stock_min	Minimum material stock in kilograms
material_stock_max	Maximum material stock in kilograms
material_stock_p5	5th percentile value of material stock in kilograms
material_stock_p95	95th percentile value of material stock in kilograms
material_stock_std_pct	Relative standard deviation of material stock in %

Using the dataset, it was possible to determine the material types aggregated by building type and cohort across 357 municipalities in Norway (Fig. 1a, 1b). The most dominant material type nationwide is concrete surrogate, accounting for 139.3 Mt of stock, with SFH as the primary contributor. This is followed by wood and wood products at 43.8 Mt, also predominantly influenced by SFH, and concrete with 39.8 Mt, where AB hold the largest share. The remaining materials have significantly lower stock volumes, with insulation and paper and cardboard each totalling 5.1 Mt and glass at 0.8 Mt, all with SFH as a dominant contributor. For each material type, the uncertainty ranges illustrated as error bars in Figures 1a and 1b, were derived from Monte Carlo simulations, as detailed in the methodology.

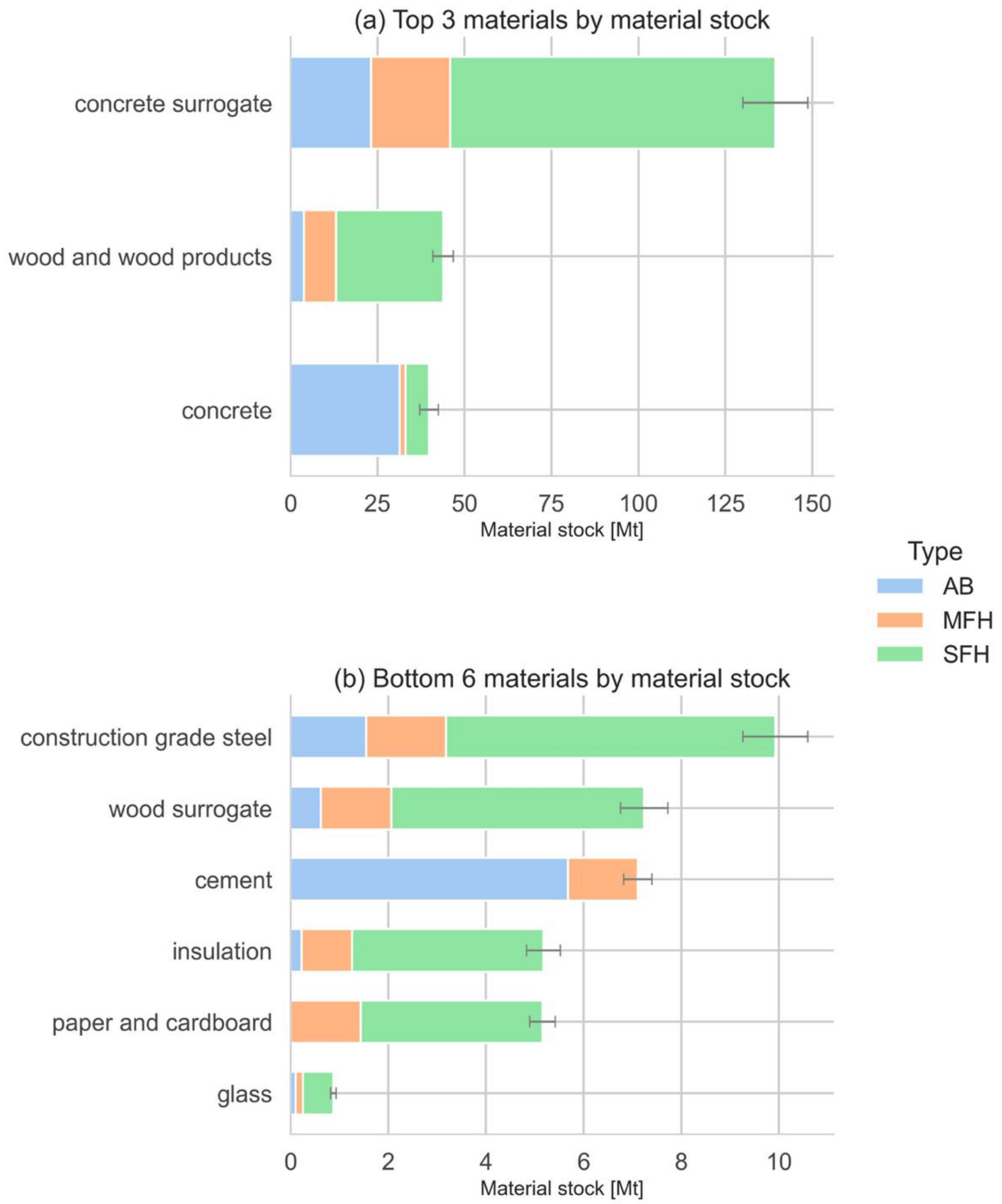


Figure 1 – Total material stock disaggregated by material types and building types (AB – apartment block, MFH – multi-family house, SFH – single-family house): (a) Three material types with the highest stock values across Norway; (b) The rest of material types present in Norway. Note the different scales in the x-axis. The error bars represent one standard deviation resulted from Monte Carlo simulations.

Similarly, it is insightful to examine which building cohorts contribute most to the stock of the top three material types (concrete surrogate, wood and wood products, concrete) to better understand the potential availability of secondary materials following building reconstruction (Fig. 2). It is evident that the oldest cohorts (1955 and 1956–1970) account for the largest share of all three material types. Notably, for concrete surrogate, approximately 80% of the total stock originates from buildings constructed between 1955 and 1990.

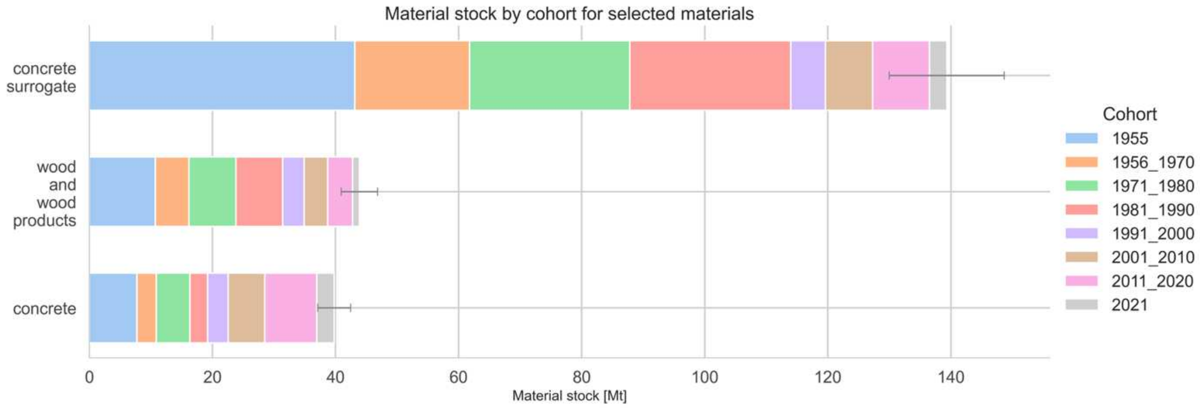


Figure 2 – Material stock of the three most prevalent material types (concrete surrogate, wood and wood products, concrete) in Norway, disaggregated by construction cohort. The error bars represent one standard deviation resulted from Monte Carlo simulations

4.1.3 Material stock distribution across Norwegian municipalities

It was important to visualize and examine the geographical distribution of specific material types as well as overall material stock totals. This facilitated the identification of municipalities with the highest contributions to material stocks. For instance, mapping the total material stock based on the mean values obtained after running Monte Carlo simulations, (Fig. 3) provides a comprehensive overview of the material intensity across Norwegian municipalities, offering new perspectives for national-scale resource management and circular economy planning. The map clearly indicates that the highest concentration of material stock is located in Oslo municipality (29.9 Mt), followed by Bergen (13.2 Mt) and Trondheim (10.3 Mt). These municipalities are the largest and most densely populated in Norway, which explains their substantial material stock levels. It is also evident that surrounding municipalities show higher material stock compared to those in the central and northernmost parts of the country. In northern Norway, Tromsø stands out as another urban center with notably higher material stock values, reflecting its role as a major regional hub.

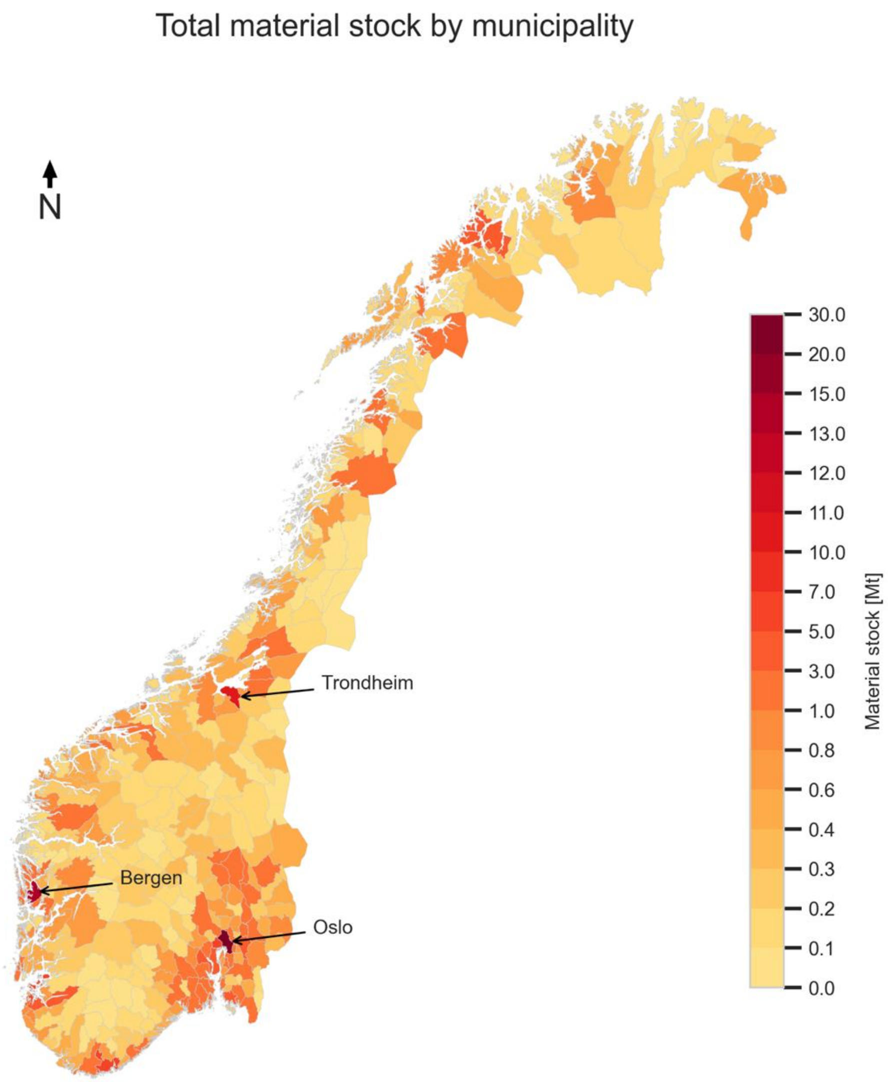


Figure 3 – Geographical distribution of material stock totals (in megatons) in 357 municipalities in Norway.

A similar geographical pattern emerges when examining the distribution of specific material types. For instance, exploring the stock of concrete surrogate, the most prevalent material in residential buildings across Norway, can reveal regional variations. Similarly, mapping construction-grade steel, a highly carbon-intensive material, highlights areas where related emissions may be most concentrated. These spatial patterns can be readily visualized and explored through the interactive dashboard developed for this study, which will be described in detail in the next section of this chapter.

4.1.4 Comparison with previous study

Material stock data was available in kilograms per material type, categorized by building type, construction cohort and municipality, presenting the first country-wide quantification of residential material stocks at such level. However, to ensure the reliability, mean values for selected material totals per capita were compared with findings from the study by Rousseau et al. (2025), which focused on Oslo and surrounding municipalities. Minor differences appeared across municipalities, while larger discrepancies in Oslo likely stem from methodological choices in floor area estimation (heated vs. total), particularly since AB dominate the city's stock. Overall, the comparison showed strong alignment in spatial distribution and consistent contributions of SFH, MFH and AB to material stocks per capita (see Fig. 4).

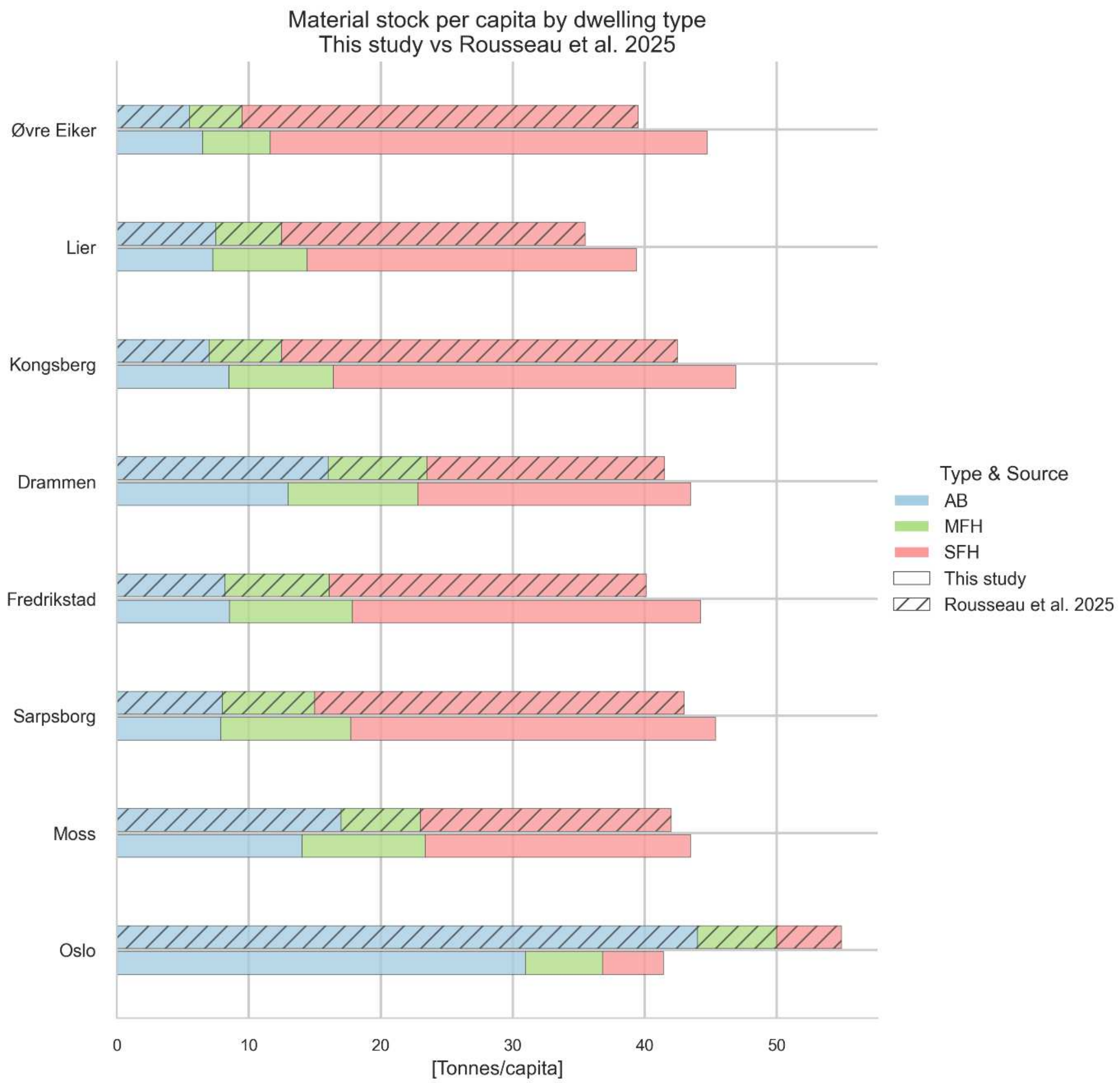


Figure 4 – Comparison of material stock totals per capita (in tons/capita) by building type (AB – apartment block, MFH – multi-family house, SFH – single-family house), obtained from this study and from Rousseau et al. (2025) for selected municipalities.

4.2 Embodied GHG emissions

The datasets containing emissions from material production (Table 5) and emissions from manufacturing (Table 6) were kept separate initially due to differences in their structure. However, for the purpose of analyzing total embodied emissions at the municipal level, both datasets were subsequently merged (Table 7) to enable comprehensive assessment. As in case of material stock, the emissions data in all three datasets were stored in kg CO_2e. The datasets are also available in the Zenodo repository (Dolgaya et al. 2025).

Table 5 – The structure of the dataset containing statistical results on embodied GHG emissions from material production, by building type, cohort and material type at municipal level in Norway; ‘kommunenum’ (Norw.) refers to the municipal code

Attribute	**Description**
type	Type of dwelling, coded as AB (apartment block), MFH (multi-family house), SFH (single-family house)
cohort	Class of the periods of dwelling construction
kommunenum	Municipality code
material	Material type (cement, glass etc.)
material_emissions_mean	Mean material production emissions in kg CO_2e
material_emissions_min	Minimum material production emissions in kg CO_2e
material_emissions_max	Maximum material production emissions in kg CO_2e
material_emissions_p5	5^{th} percentile value of material production emissions in kg CO_2e
material_emissions_p95	95^{th} percentile value of material production emissions in kg CO_2e
material_emissions_std_pct	Relative standard deviation of material production emissions in %

Table 6 – The structure of the dataset containing statistical results on embodied GHG emissions from manufacturing processes, by building type, cohort and energy carrier at municipal level in Norway; ‘kommunenum’ (Norw.) refers to the municipal code

Attribute	**Description**
type	Type of dwelling, coded as AB (apartment block), MFH (multi-family house), SFH (single-family house)
cohort	Class of the periods of dwelling construction
kommunenum	Municipality code
energy_carrier	Energy carrier type (electricity, gasoline etc.)
manufacturing_emissions_mean	Mean manufacturing emissions in kg CO_2e
manufacturing_emissions_min	Minimum manufacturing emissions in kg CO_2e
manufacturing_emissions_max	Maximum manufacturing emissions in kg CO_2e
manufacturing_emissions_p5	5^{th} percentile value of manufacturing emissions in kg CO_2e
manufacturing_emissions_p95	95^{th} percentile value of manufacturing emissions in kg CO_2e
manufacturing_emissions_std_pct	Relative standard deviation of manufacturing emissions in %

Table 7 – The structure of the dataset containing statistical results on total GHG emissions (from material production and manufacturing processes), by type and cohort at municipal level in Norway; ‘kommunenum’ (Norw.) refers to the municipal code

Attribute	**Description**
type	Type of dwelling, coded as AB (apartment block), MFH (multi-family house), SFH (single-family house)
cohort	Class of the periods of dwelling construction
kommunenum	Municipality code
total_mean	Total emissions in kg CO_2e
total_std_pct	Relative standard deviation in %

4.2.1 Emissions from material production

When examining emissions resulting from material production, it was particularly insightful to identify which material types, building types and construction cohorts contributed the most. As shown in Figure 5a, construction-grade steel emerges as the largest contributor to production-related emissions, accounting for approximately 21.8 Mt CO_2e, despite its material stock being relatively low compared to materials such as concrete surrogate or wood and wood products. In contrast, emissions from concrete surrogate and wood and wood products are significantly lower, at 0.56 Mt CO_2e and 5.35 Mt CO_2e, respectively (Fig. 5b). Other notable contributors include cement and insulation materials, contributing around 6 and 5.85 Mt CO_2e respectively, while concrete contributes minimally with only 0.16 Mt CO_2e. Across all material categories, the uncertainty ranges displayed in the figure, represented as error bars, capture the variability introduced through the Monte Carlo simulations.

Among the building types, SFHs are the dominant contributor to emissions, reflecting their status as the primary contributor to total material stock. This is expected, as emissions and material stock are generally linearly correlated. There is no contribution from SFH in cement-related emissions, nor from ABs in paper and cardboard, due to the absence of these materials in the composition of those building types. Similarly, emissions from concrete production are associated with ABs that utilize this material a lot.

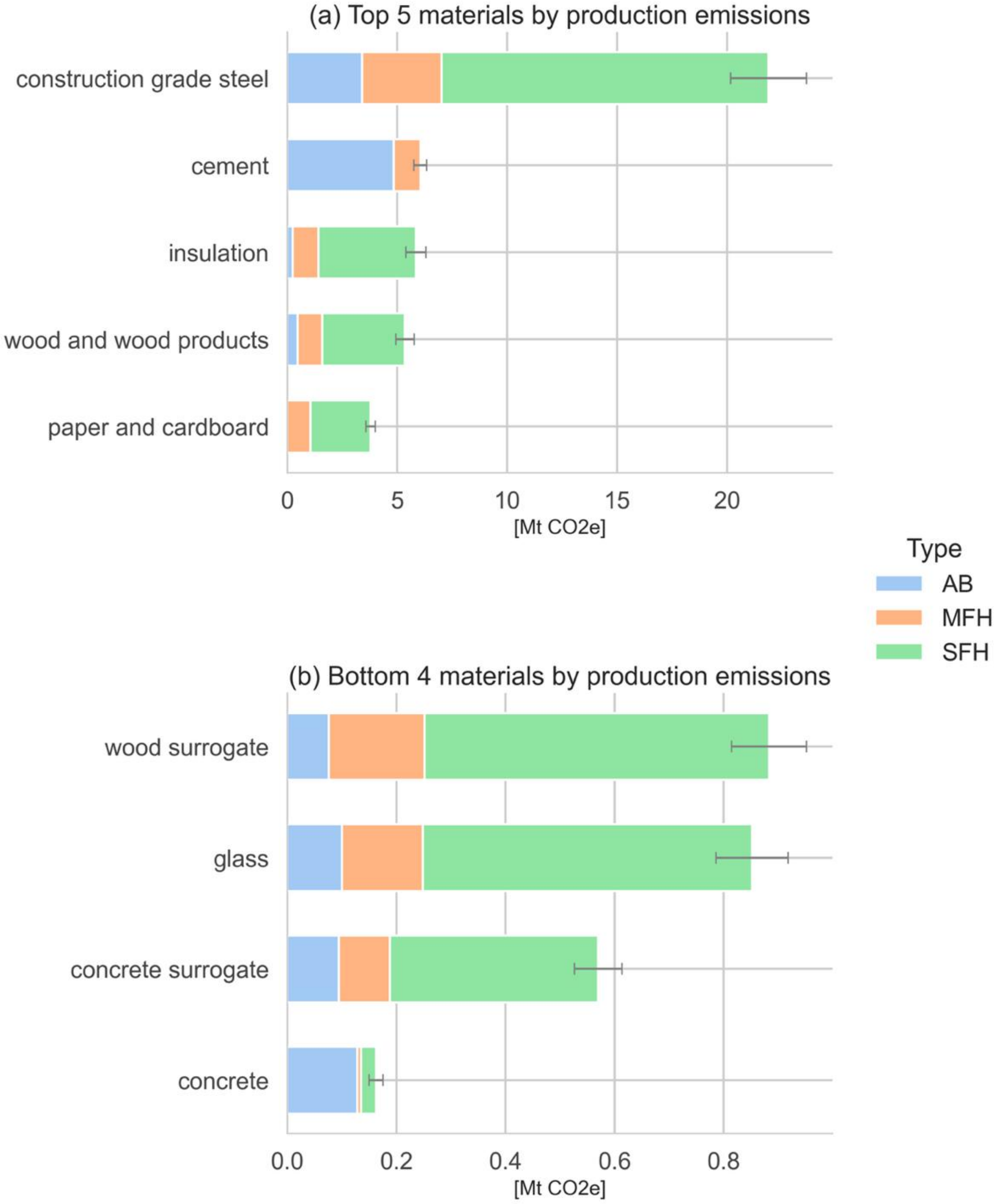


Figure 5 – Embodied GHG emissions resulted from material production, disaggregated by material types and building types (AB – apartment block, MFH – multi-family house, SFH – single-family house): (a) Three material types with the highest emission totals values across Norway; (b) Emissions from the rest of material types present in Norway. Note the different scales in x-axis. The error bars represent uncertainty ranges resulted from Monte Carlo simulations.

Regarding construction cohorts (Fig, 6), the contribution to emissions follows a consistent trend, with older cohorts emerging as the primary contributors. This pattern is expected, as emissions from material production are directly related to the corresponding material stock, which is highest in older buildings. There is no substantial variation in cohort shares across different material types, as the emission factors used in this analysis were assumed to be constant across all construction periods. Although in reality, material production technologies have evolved significantly since the mid-20th century, potentially affecting emission intensities (Greening et al. 1998), reliable and geographically relevant historical data was not available to reflect these changes in the analysis. Therefore, a uniform emission intensity was applied across cohorts for consistency and comparability.

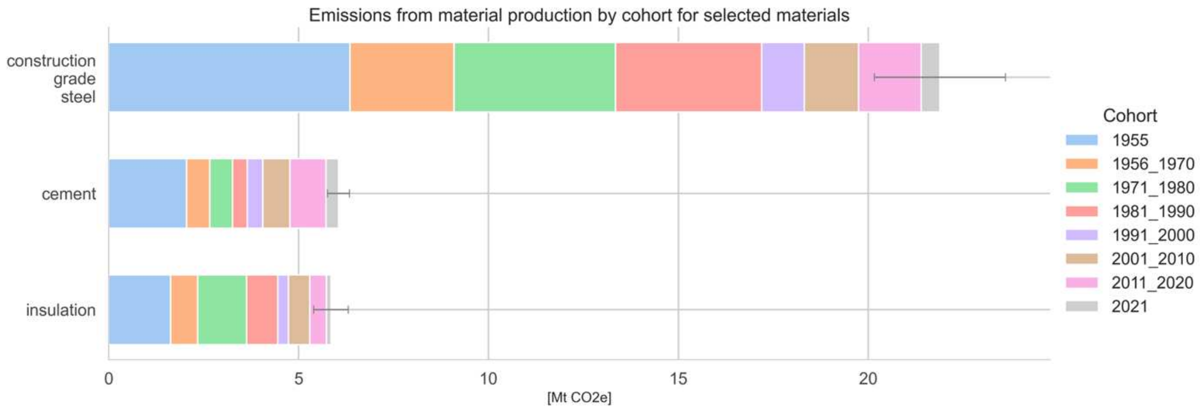


Figure 6 – Embodied GHG emissions from production of the three most prevalent material types (construction grade steel, cement, insulation) in Norway, disaggregated by construction cohort. The error bars represent uncertainty ranges resulted from Monte Carlo simulations.

4.2.2 Emissions from manufacturing

Embodied GHG emissions from manufacturing processes show variation across building types rather than material types. While the absolute values of manufacturing emissions are lower compared to those from material production, they still offer interesting observations. As illustrated in Figure 7, manufacturing associated with SFHs contributes the largest share of emissions, totaling 2.28 Mt CO_2e, followed by MFHs with 0.57 Mt CO_2e and ABs with 0.51 Mt CO_2e when exploring the mean values. This distribution is primarily due to the larger number of SFHs across the country, rather than differences in manufacturing intensities. In fact, the same manufacturing intensity values were applied across all building types, with the exception of SFHs, which include natural gas usage in the manufacturing stage. Across all categories, gasoline emerged as the dominant emission source.

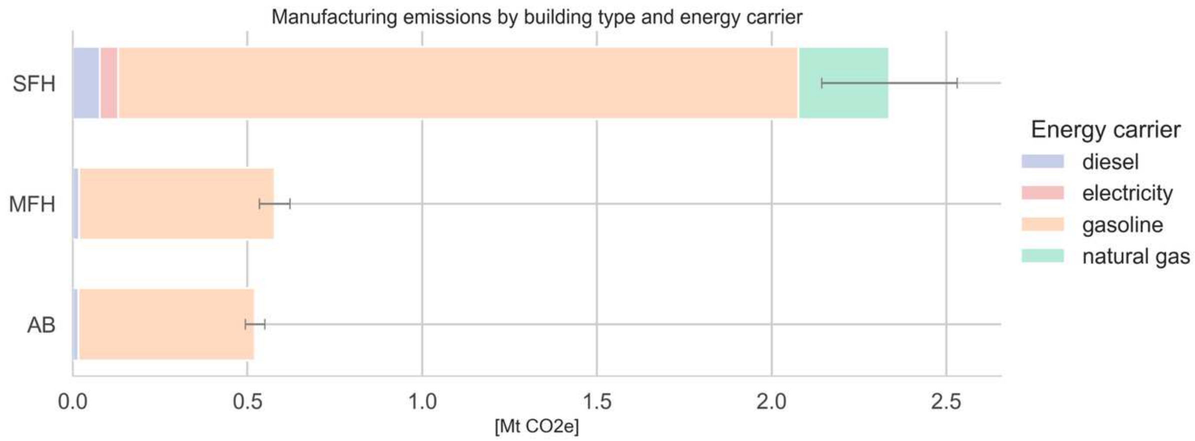


Figure 7 – Embodied GHG emissions from manufacturing processes in Norway, disaggregated by energy carrier and building type (AB – apartment block, MFH – multi-family house, SFH – single-family house). The error bars represent uncertainty ranges resulted from Monte Carlo simulations.

4.2.3 Total emissions

Total embodied GHG emissions in this study represent the combined sum of emissions from material production and dwelling manufacturing at the municipal level. Mapping these emissions provides valuable insights into the spatial distribution of embodied carbon, especially when applying a consumption-based carbon accounting approach. This approach attributes emissions to the municipality where the material was used and the dwelling constructed, rather than the location of the actual emission release which, particularly for material production, is often outside Norway.

As illustrated in Figure 8, the spatial distribution of total emissions closely mirrors that of total material stock, which is expected given that material production is the dominant contributor to total emissions. Since emissions are directly related to the quantity of material stock, municipalities with larger stocks also exhibit higher emissions. For example, Oslo accounts for approximately 5 Mt CO_2e, followed by Bergen (2.4 Mt CO_2e) and Trondheim (1.8 Mt CO_2e). Surrounding municipalities also show elevated emissions, in contrast to the central and northern regions of Norway, where both material stock and emissions are significantly lower.

Total emissions by municipality

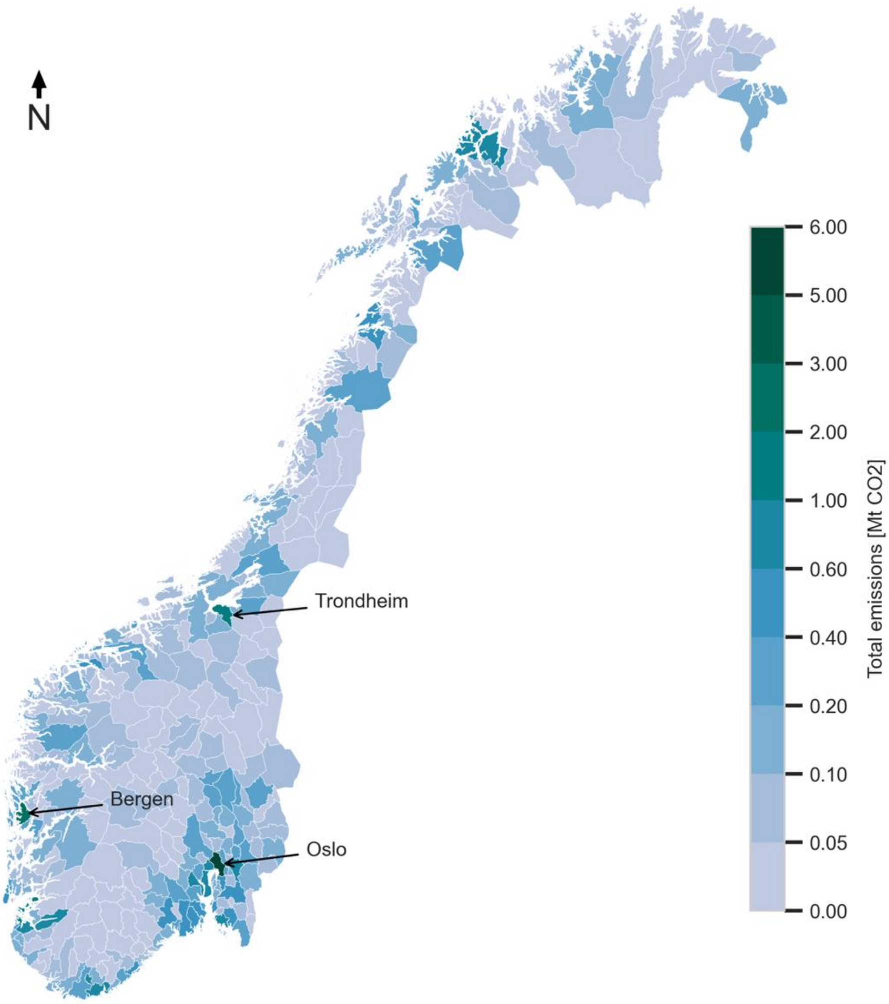


Figure 8 – Geographical distribution of total GHG emissions (in megatons CO_2e) in 357 municipalities in Norway.

It is also informative to examine per-capita total emissions at the municipal level, as this provides insight into which areas exhibit the highest and lowest emissions intensities, and what factors may be driving these patterns. When observing the top 10 municipalities by per-capita emissions (Fig. 9a), a consistent trend emerges across all of them. Per-capita emissions, represented by the mean values, range from approximately 13.7 to 17 tonnes CO_2e per person, with the single-family house building type contributing the vast majority of these values. In contrast, the presence of multi-family house and apartment blocks is either minimal or entirely absent, as seen in Leka municipality, where no AB dwellings are present. This pattern indicates that municipalities with the highest per-capita emissions are typically rural, characterized by low population density and a dominance of SFH structures. For instance, the population of Osen in 2024 was 895, Leka 598 and Ibestad 1300. The remaining municipalities in the top 10 list also had populations ranging from approximately 500 to 1400 residents. These figures underscore how low population combined with relatively high material stock, particularly from SFH, results in elevated per-capita emissions, even if the total emissions remain moderate.

In contrast, the bottom 10 municipalities by per-capita emissions (Fig. 9b) demonstrate a markedly different pattern. These municipalities show significantly higher shares of apartment blocks and multi-family houses, indicative of more urbanized areas with higher residential density. The per-capita emissions based on mean values in these municipalities range between approximately 6.5 and 7.5 tonnes CO_2e, which is substantially lower compared to the municipalities ranked highest in per-capita emissions. This difference can largely be attributed to the more efficient use of materials per resident in dense urban housing types such as AB and MFH, in contrast to material-intensive SFHs. Additionally, these municipalities have considerably larger populations, often in the range of tens of thousands, with Oslo reaching a population of 723196 in 2024. The combination of higher population figures and compact housing typologies leads to a lower average material use and emissions per capita, highlighting the potential benefits of urban density in reducing environmental impact.

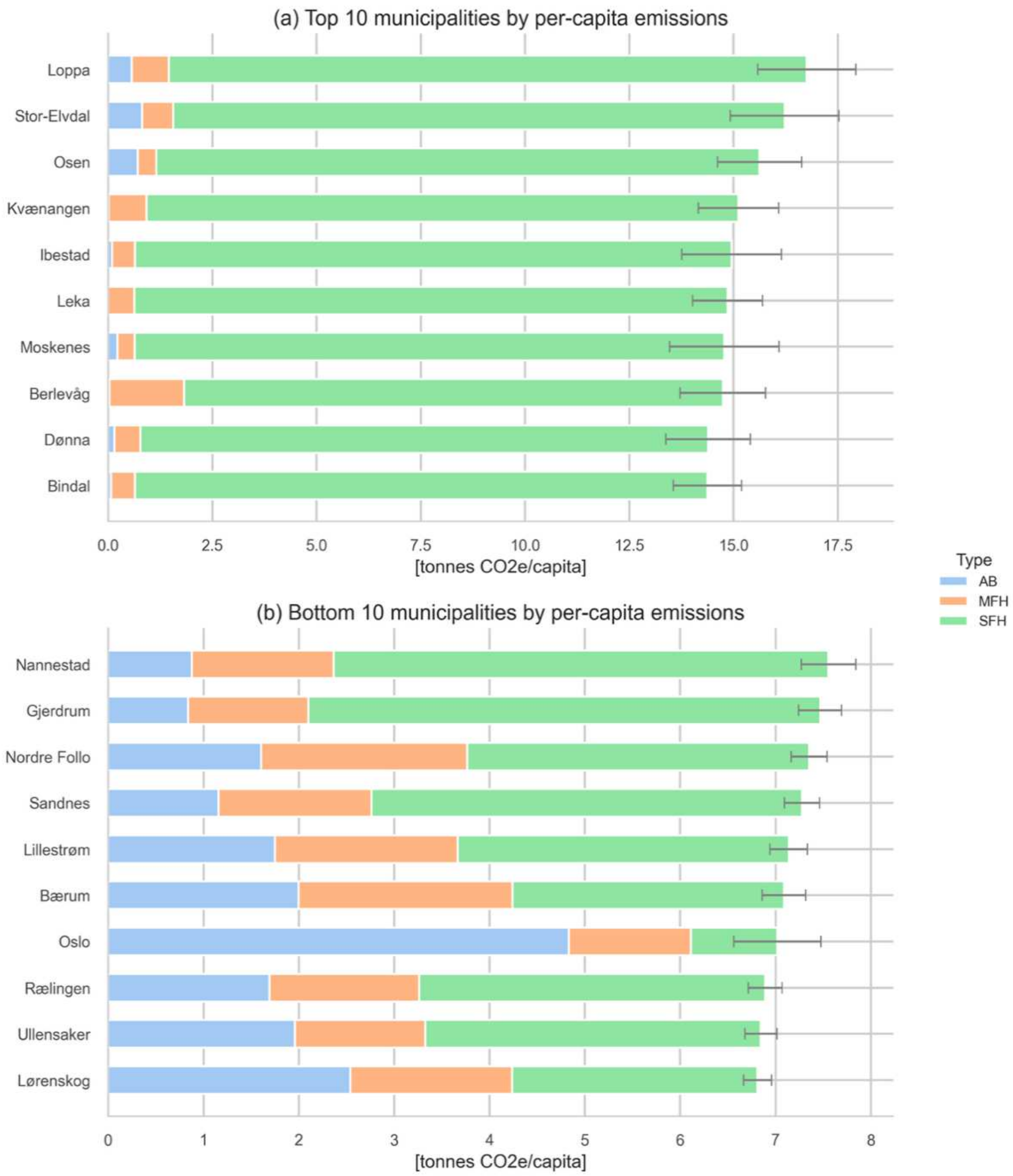


Figure 9 – Total GHG emissions per capita, disaggregated by building type (AB – apartment block, MFH – multi-family house, SFH – single-family house): (a) Ten Norwegian municipalities with the highest per-capita emissions; (b) Ten Norwegian municipalities with the lowest per-capita emissions. Note the different scales in the x-axis. The error bars represent uncertainty ranges resulted from Monte Carlo simulations.

To further explore and contextualize these trends, it is useful to examine the capita-per-dwelling ratio across selected municipalities. For example, in more rural municipalities with higher per-capita emissions, this ratio is typically around 1.5, indicating lower household occupancy and a predominance of SFHs. This suggests a greater material and emissions intensity per resident, as more building material is used per person.

In contrast, more urban and densely populated areas show a capita-per-dwelling ratio closer to 2.5, reflecting higher household occupancy levels and more compact housing forms such as ABs and MFHs. This results in more efficient material use per capita and consequently lower emissions per resident, again underlining the environmental advantages of higher-density residential development.

4.2.4 Comparison with previous studies

The International Energy Agency Energy, through its Building and Communities ("EBC Annex 57 Results," 2016), analyzed over 80 building case studies and found that building material-related emission intensities ranged between 20–620 $kgCO_2e/m^2$ for construction stages (Module A1–A3). Although this range is quite broad due to variation in building type, material choice and construction methods, the mean values obtained in this study, ranging between 150 and 210 $kgCO_2e/m^2$, fall well within this international benchmark (Fig. 10). This metric highlights the relative carbon intensity of building materials in the Norwegian context, emphasizing both the relevance of the local building stock characteristics and the importance of material efficiency strategies. It also reinforces the need for targeted mitigation measures, especially within the dominant building types contributing most to overall emissions.

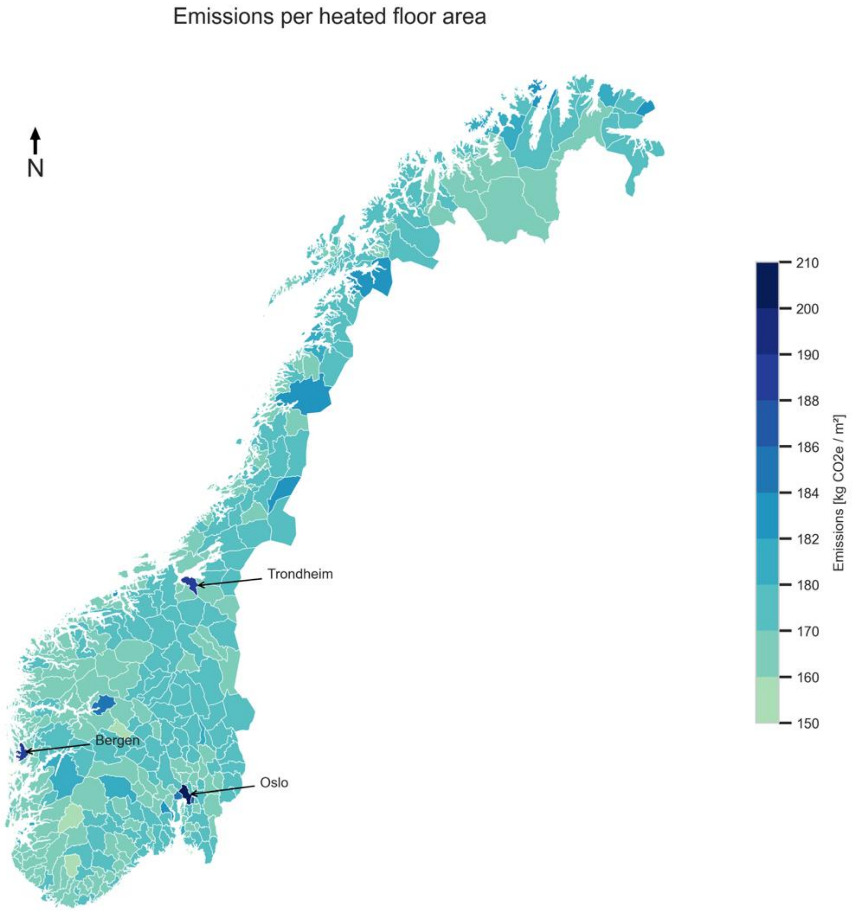


Figure 10 – Geographical distribution of total GHG emissions per heated floor area (in kilogram CO_2e/m^2) at municipal level in Norway.

Furthermore, in 2023, emissions from residential building operations (primarily heating) amounted to 0.6 Mt CO_2e per year (Norwegian Environment Agency 2024). In comparison, the embodied emissions from material production and dwelling manufacturing for newly built residences (2021 cohort representing residential houses built from 2021 t0 2024) reached 0.32 Mt CO_2e per year. While these values are of a similar order of magnitude, they represent fundamentally different sources: operational emissions reflect the entire existing building stock, whereas embodied emissions only account for the most recent construction. This comparison underlines both the relative scale and the complementary nature of operational and embodied impacts.

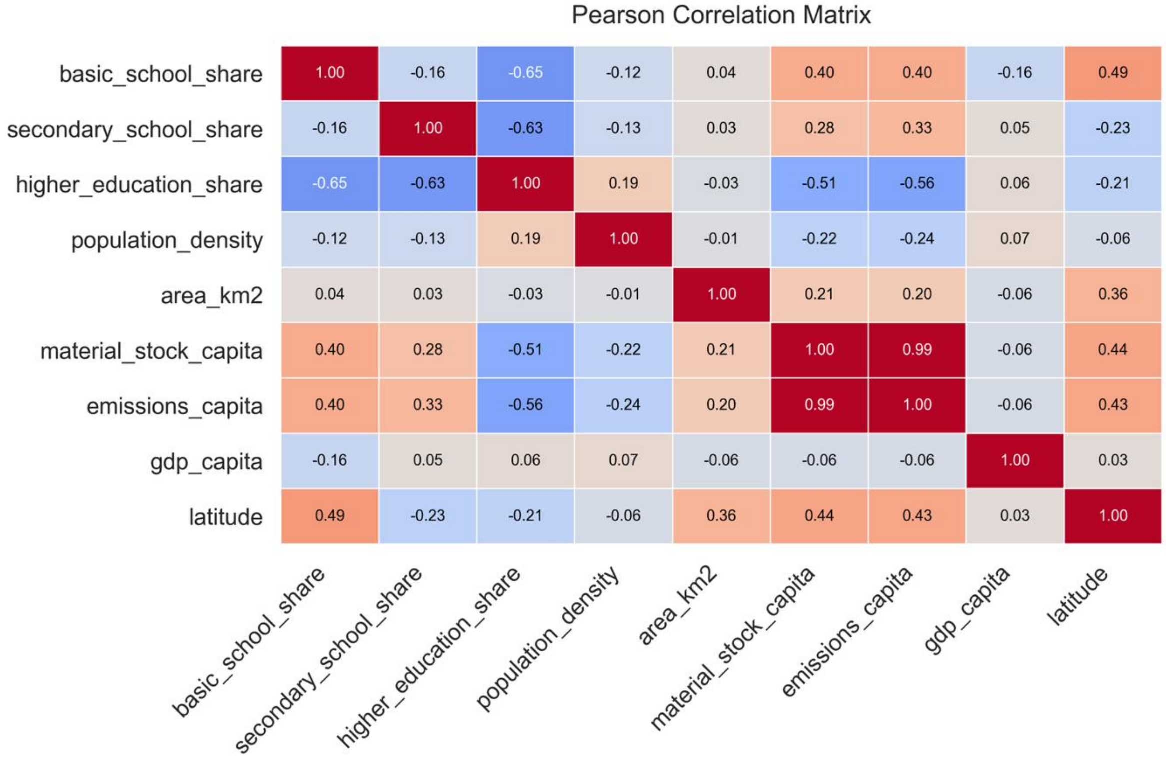
4.3 Material stock, GHG emissions and spatial and socio-economic characteristics of municipalities

To better understand the possible drivers of total material stock and embodied GHG emissions across Norwegian municipalities, a statistical analysis using Principal Component Analysis (PCA) was conducted. The goal was to identify underlying patterns and relationships between material and emission intensities and a range of socio-economic and geospatial variables, including education levels, GDP per capita, population density, municipal area and latitude. These relationships may help explain regional disparities and drivers of material use and environmental impact.

The Pearson correlation matrix (Figure 11) presents the coefficients of linear relationships between selected socio-economic and geographical variables and illustrates the linear relationships between the selected variables. The matrix with biplots between all variables is presented in the Annex, Figure A2. There are several notable associations emerged:

1. Material stock per capita correlates positively with emissions per capita ($r = 0.99$), and both these variables correlate with the basic school share ($r = 0.44$ and $r = 0.43$ respectively), suggesting that municipalities with lower education levels may exhibit higher infrastructure accumulation and carbon intensity.
2. A moderate positive correlation is also observed between material stock and latitude ($r = 0.44$), and emissions per capita and latitude ($r = 0.43$), indicating that municipalities located farther north tend to have higher material consumption and carbon emissions per capita.
3. Latitude shows a moderate positive correlation with basic school share ($r = 0.49$), suggesting a possible geographical gradient in educational attainment, with northern regions having a higher proportion of residents with only basic education.
4. A strong negative correlation is evident between basic and higher education share ($r = -0.65$), and secondary school share and higher education share ($r = -0.63$), reinforcing the inverse relationship between lower and higher education levels across municipalities in Norway.
5. A modest positive correlation between higher education share and population density ($r = 0.19$), indicating that more densely populated municipalities tend to have more people with higher

education.



	basic_school_share	secondary_school_share	higher_education_share	population_density	area_km2	material_stock_capita	emissions_capita	gdp_capita	latitude
basic_school_share	1.00	-0.16	-0.65	-0.12	0.04	0.40	0.40	-0.16	0.49
secondary_school_share	-0.16	1.00	-0.63	-0.13	0.03	0.28	0.33	0.05	-0.23
higher_education_share	-0.65	-0.63	1.00	0.19	-0.03	-0.51	-0.56	0.06	-0.21
population_density	-0.12	-0.13	0.19	1.00	-0.01	-0.22	-0.24	0.07	-0.06
area_km2	0.04	0.03	-0.03	-0.01	1.00	0.21	0.20	-0.06	0.36
material_stock_capita	0.40	0.28	-0.51	-0.22	0.21	1.00	0.99	-0.06	0.44
emissions_capita	0.40	0.33	-0.56	-0.24	0.20	0.99	1.00	-0.06	0.43
gdp_capita	-0.16	0.05	0.06	0.07	-0.06	-0.06	-0.06	1.00	0.03
latitude	0.49	-0.23	-0.21	-0.06	0.36	0.44	0.43	0.03	1.00

Figure 11 – Pearson correlation coefficients between the variables added to the exploratory PCA analysis of material stock per capita.

To uncover broader patterns, a PCA was conducted. PCA loadings, representing the correlation between original variables and the principal components, were used to interpret the main dimensions of variation in the dataset. In this analysis, the first three components accounted for a substantial proportion of the total variance (Figure A1), with the first two components alone capturing sufficient structure to support meaningful interpretation, that is why this was an optimal number of components to retain.

Principal Component 1 (PC1) accounts for 36.8% of the total variance and is primarily influenced by higher education share, GDP per capita and population density (Figure 12). This axis reflects a socio-economic development dimension, separating more urbanized and educated municipalities from less developed ones. Principal Component 2 (PC2) explains 17.4% of the variance and is more closely associated with latitude, municipal area, material stock per capita, emissions per capita and basic school share. This component represents a geographic–environmental dimension, distinguishing municipalities based on location, spatial structure and environmental intensity.

Variables such as higher education share and population density are closely aligned, pointing toward the positive end of PC1, reinforcing their shared role in defining socio-economic status. Conversely, basic school share and latitude are grouped along PC2, suggesting a spatial pattern in lower educational attainment. Secondary school share appears in the opposite direction of higher education share, aligning with the negative correlation found in the Pearson matrix; material stock and emissions per capita vectors are strongly aligned and contribute predominantly to PC2, indicating a shared structural-environmental dimension.

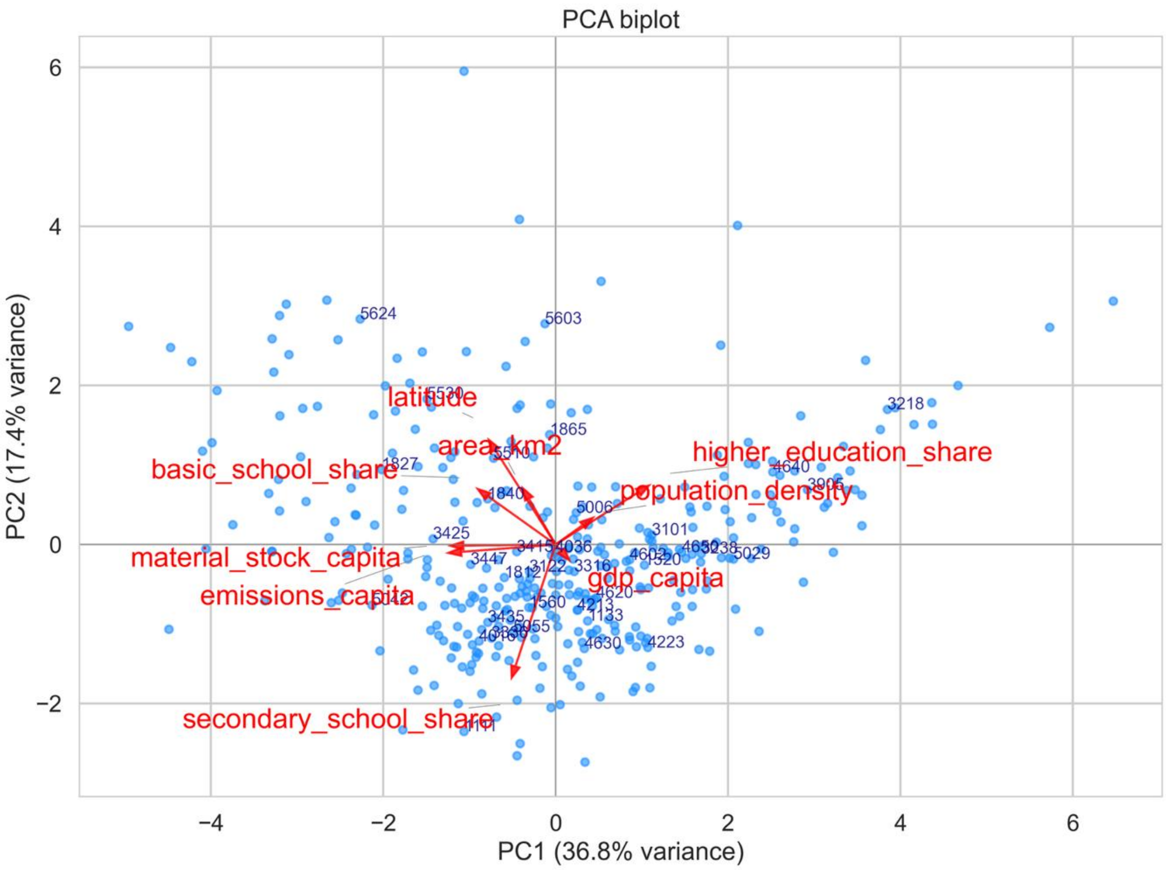


Figure 12 – First factorial plane of the PCA analysis.

These components reveal independent patterns, where municipalities with higher education and population density exhibit distinct profiles compared to more rural municipalities that are characterized by higher material stocks and emissions per capita.

The PCA results highlight three main structuring dimensions among Norwegian municipalities. Component 1 contrasts urbanized, higher-educated municipalities with lower material stocks and emissions per capita against rural, northern municipalities with higher emissions and material intensity. Component 2 reflects a regional gradient, where northern, larger-area municipalities with somewhat dominant higher-education shares are distinguished from those with stronger secondary-school shares. Component 3 emphasizes economic development, with higher GDP per capita opposed to reliance on basic education. Together, these axes highlight spatial, socio-economic and environmental clustering that shape municipal characteristics.

These findings underscore the interconnected different dimensions that structure municipal characteristics in Norway. The combination of correlation analysis and PCA offers a robust framework for interpreting how different factors co-vary and contribute to material and emission outcomes.

4.4 Communication via dashboard

Dashboard allows for a quick and transparent access to the data (Fraser and Gao 2025) for effective communication of the results mentioned in the previous chapters of this work. It provides a comprehensive toolset that supports evidence-based decisions, policies and other outcomes related to sustainable building practices, resource efficiency and emissions reduction.

To enable efficient interaction with the dashboard, a denormalized dataset was created by merging the statistical metrices on material stock, emissions from material production and emissions from manufacturing into a single unified structure. This integrated format facilitates streamlined analysis and visualization across spatial and typological dimensions within the dashboard environment.

4.4.1 Dashboard application

The most recent version of the dashboard is available in the GitHub repository [https://github.com/DolgayaMaria/materials_emissions_dashboard]. The repository includes a README file containing detailed information on the dataset and its attributes, instructions for running the dashboard application and a description of its intended use.

Examples of dashboard application screenshots are provided in the Annex of this work (Figure A1-A3) to illustrate the overall layout, key features, and usability of the tool.

4.4.2 Dashboard use scenarios

The dashboard is designed to accommodate multiple use cases, depending on the needs of user groups and their specific analytical goals. The table below (Table 9) summarizes various user groups, their possible objectives and questions, key features of the dashboard that might be useful to assess them and a short description of the actions and decision-making steps and outcomes that the data and information acquired from the dashboard could support. In addition, each use case can be further enriched by incorporating a metric of interest that reflects different scenarios, such as a real-life scenario, worst-case scenario or best-case scenario, corresponding to the mean, maximum or minimum values derived from the Monte Carlo simulations, respectively.

Table 8 – Potential identified dashboard use scenarios based on a user group and their objectives, showing useful features and interactive tools which can be helpful for achieving possible outcomes

User group	Objective	Dashboard features	Possible outcomes
Policy	Identify municipalities	Choropleth maps of	Target policies for emission

makers	and material types contributing most to material stocks and emissions	material stock and emissions at municipal level	reduction, implementing circular economy strategies
Municipal advisors	Benchmark material stock and emissions at their municipality	Filter tool to downscale to a specific municipality	Local sustainability strategies towards circularity legislation
Urban planners	Explore spatial distribution and trends in material stock	Maps of material stock by material type, charts with building types / cohort breakdown	Plan for sustainable development, renovation and demolishing
Researchers	Find correlations between material stock and emissions based on different scenarios	Raw data exploration, charts with building type / cohort / energy carrier breakdown, scenario exploration	Further academic analysis and scenario modelling
Construction companies / industries	Explore the contribution of various building types and cohorts in material stock across municipalities	Maps by material type, charts with building type / cohort breakdown	Identification of business opportunities in recycling and reuse markets

As a specific user-case example, the following case could be considered for visualization purposes: a user is a municipal advisor of Trondheim whose objective is to analyse the emissions from material production of construction grade steel based on the current material stock in their municipality in all cohorts. To check that, the user will run the dashboard application; then select Real-Life Scenario in (1) Select Scenario field; select Material Production Emissions field in (2) Select Output section; downscale to the municipality of Trondheim by clicking on it on the map in Select Municipality (3); click on 'Construction Grade Steel' in the (4) Select Material Type section on the right; there is no need to select any specific archetype in (5) Select Type and Cohort section since it is not the point of interest in this case. These steps will lead to the values of the user's request (Figure 13). In this case, the result will appear as a text message on the top of the screen saying 'Construction Grade Steel material production emissions in Trondheim – Tråante: 761.4 kt CO_2e '. Depending on the case and objective, results may be observed on the map and/or the bar charts themselves.

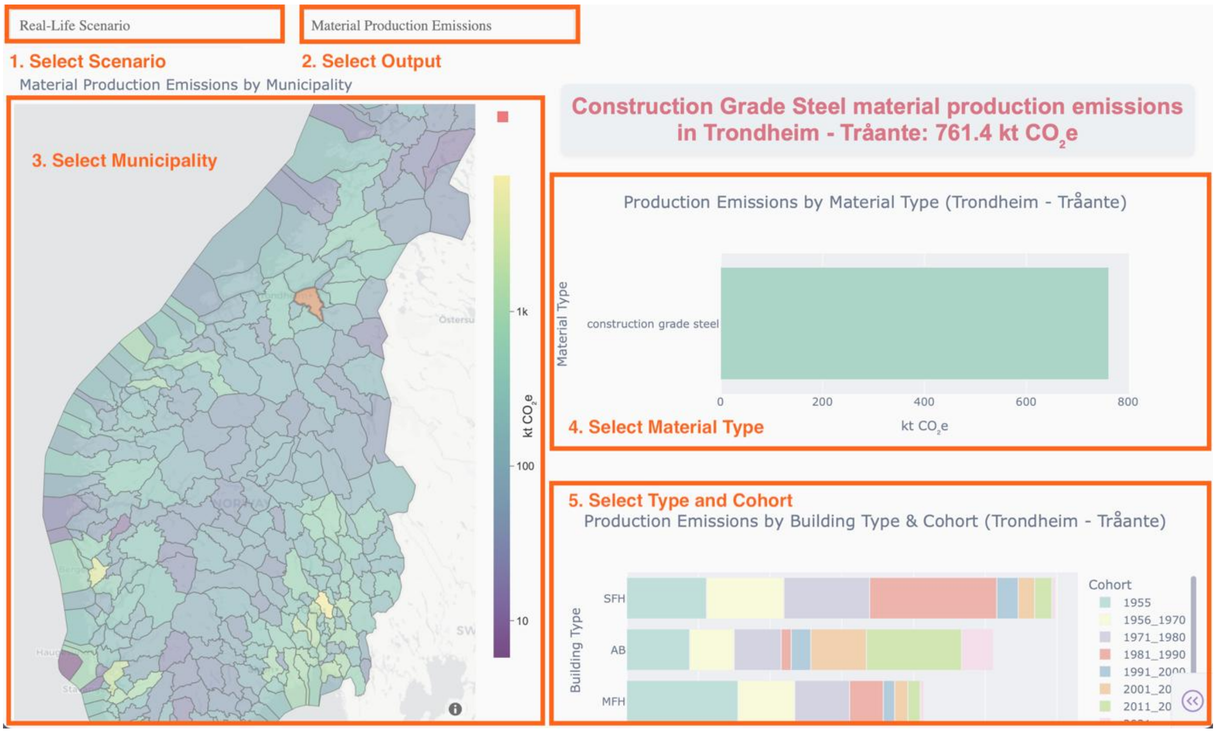


Figure 13 – The layout of the dashboard interface. Numbered labels, highlighted in red, indicate a sequence of selection fields of the steps of an usual dashboard consultation. The interface allows downscaling to municipalities, archetypes (types and cohorts), material types and energy carriers.

5. Discussion

5.1 Research questions addressed

The main objective of this study was to analyze the distribution and composition of material stocks in residential buildings across Norwegian municipalities and to assess the embodied GHG emissions associated with material production and building manufacturing. Particular attention was given to manufacturing, one of the LCA stages which have received comparatively less focus in efforts to reduce GHG emissions (Lausselet et al. 2020). The analysis was carried out with an emphasis on ensuring that the results can be effectively visualized and that the approach remains adaptable for replication in future studies and application in different contexts. This study was guided by four detailed research questions, all of them were answered:

1. **What materials make up Norway's residential building stock, how are they distributed by municipality, and which materials, typologies and cohorts dominate?**
   The analysis revealed that concrete surrogate accounts for the largest share of material stock (139.3 Mt), particularly associated with single-family houses and older cohorts (1955, 1956–1970) which are dominant across municipalities and together represent 28.1% of the total material stock. Geographical distribution showed higher concentrations of materials in Norway's largest urban centers such as Oslo (11.6%) and Bergen in the south of the country (5.1%), Trondheim in its central part (3.9%) and Tromsø in the north (1.6%).

2. **Which materials, typologies, cohorts and energy carriers drive the most embodied GHG emissions in Norway's residential sector?**
   Despite concrete surrogate dominating stock volume, construction-grade steel emerged as the main contributor to embodied GHG emissions (21.8 Mt CO_2e) due to its high carbon footprint (Pauliuk et al. 2021). Gasoline used in single-family houses manufacturing was the most dominant energy carrier in terms of manufacturing emissions (87.6%).

3. **What are the total embodied GHG emissions from Norway's residential buildings, how are they geographically distributed, and how do they vary per capita and per heated floor area?**
   Emissions followed the same geographic pattern as material stock, with the highest values in major urban municipalities. Per capita emissions were found to be higher in rural areas, largely due to the prevalence of single-family homes and lower population densities, this is in line with previous findings (Rousseau et al. 2025), with the highest values from around 13.7 to 17 tonnes CO_2e per person. The statistical analysis also revealed that total material stock and total GHG emissions shares strongly aligned with each other, defining a geographic–environmental dimension (PC2), suggesting a strong link between material intensity and environmental impact, particularly in less

urbanized or structurally expansive areas.

4. **How can spatial and categorical patterns of material stocks and embodied emissions be communicated via an interactive dashboard to support different user needs and decisions, and how can the analytical framework be replicated elsewhere?**
   An interactive and user-friendly dashboard was developed to communicate results in a transparent and accessible way and facilitate easy access and visualization of data and results for several user types. It enables multiple user scenarios (real-life, best-case and worst-case), supporting both research applications and stakeholder decision-making and based on high-level libraries, like Dash and Plotly, which combine ease, speed and power in the implementation of data science projects. Beyond visualization, the workflow itself is designed as a modular and adaptable data science framework. The adoption of an ontology, as done in this study, facilitates this possibility, by allowing the use of terms and concepts formally defined and openly available. With appropriate regional data, the methodology could serve as a blueprint for comparable studies elsewhere. In an early stage of this study, it was considered the possibility to develop two use cases using the framework, one for Norway, as performed, and another for Portugal. However, it was not possible to identify open available data for the later, either at the national statistics agency (INE) or another source. This indicates that a there is a long way to go in Portugal and other countries of the European Union until datasets on material stock become available to support an equivalent study for the country.

5.2 Relation to previous studies

The methodological approach combined municipal-level heated floor area data with material intensities differentiated by building type and construction cohort. This approach proved robust, as the resulting stock estimates aligned with earlier findings (Rousseau et al. 2025), with the exception of Oslo, where the dominance of apartment blocks introduced discrepancies. These differences may be linked to methodological choices in material stock modelling, particularly whether heated or total floor area is used as the basis. While the results are of the same order of magnitude as those reported in previous studies, direct comparisons remain challenging due to differences in geographical coverage and materials included. Nevertheless, the spatial distribution of stock composition, particularly in Oslo and surrounding municipalities, showed clear parallels with existing research.

In terms of embodied GHG emissions, this study accounted for emissions from both material production and dwelling manufacturing. As the scope was limited to construction-related life cycle stages (Modules A1–A3 and A5), final values are not directly comparable with full LCA studies. Still, the magnitude of the results was consistent: material-related emission intensities ranged between 20–620 kg CO_2e/m² for Modules A1–A3 ("EBC Annex 57 Results," 2016), compared to 150–210 kg CO_2e/m² in this study. For context, operational emissions from residential buildings (primarily heating) were estimated at 0.6 Mt CO_2e per year (Norwegian Environment Agency 2024), whereas emissions from the most recent construction cohort in this study amounted to 0.3 Mt CO_2e per year.

Although several assumptions were necessary, the use of Monte Carlo simulations introduced uncertainty ranges, thereby capturing how variations in key parameters propagate through the results (Næss et al. 2025). Notably, this study represents the first nationwide quantification of residential material stocks at the municipal level. The workflow developed here is adaptable and offers a transferable blueprint for conducting similar research in other countries with comparable datasets, building typologies, and administrative structures.

5.3 Methodological contribution

The study tested multiple approaches to ensure efficient and accurate analysis. The most reliable method combined municipal-level heated floor area with differentiated material intensities by building type and construction cohort. Monte Carlo simulations were essential in adding depth to the results, allowing uncertainty ranges that cannot be derived from raw data alone. The interactive dashboard represents another data science contribution, demonstrating how advanced visualization can communicate complex datasets to diverse users in an accessible manner. These components of the work were developed with the support of large language models (LLMs), such as ChatGPT, Copilot and others, which were used to generate, review and debug Python code.

5.4 Policy and practical implications

The findings provide actionable insights into which materials and building types contribute most to embodied GHG emissions, as well as how these impacts vary geographically and per capita. By identifying the main drivers of emissions, the results support policymakers and planners in targeting interventions for emission reduction and sustainable building practices. The interactive dashboard further enhances applicability, offering a practical tool for decision-making at both municipal and national scales.

As operational energy use in buildings has been largely decarbonized in Norway, attention must now shift toward embodied and manufacturing emissions to achieve deeper mitigation. Potential strategies include improving resource and material efficiency, promoting circularity through closed material loops, and decarbonizing material production. Additionally, sufficiency measures—such as reducing per-capita floor area or encouraging policies that favour the construction of residential building types with lower embodied emissions per square meter—can further contribute to emission reductions.

5.5 Limitations

Several limitations must be acknowledged. A key challenge was the limited availability of geographically and temporally specific data for Norway. In many cases, global or generalized datasets were used, which may not fully reflect national conditions across different time periods. Material and energy intensity data were particularly scarce for older cohorts, even though these account for a large share of the current stock. Most input data lacked uncertainty ranges, which had to be synthetically generated through expert judgment for use in Monte Carlo simulations. This introduces potential bias or underrepresentation of variability across materials, cohorts and building types.

Another important limitation is the use of emission intensities based on current production methods, even when modeling older archetypes, which may not accurately reflect historical production processes and associated emissions. Floor area per dwelling data, particularly for older cohorts, were also uncertain and highly variable, adding further uncertainty to per-dwelling and per-capita estimates. Finally, the same building archetypes were applied across the entire country, which may overlook regional differences in construction practices, materials, or building sizes. These limitations should be considered when interpreting the results and when applying the methodology at a national scale.

5.6 Future research directions

Future studies should prioritize the collection and integration of region-specific historical data to improve the reliability of assessments. Increasing spatial resolution, for example through the use of cadaster data, could further enhance the accuracy of municipal-level analyses. The workflow presented here could also be applied to other countries, such as Portugal, once the necessary data become available. In addition, future research could expand the scope beyond greenhouse gas emissions to evaluate additional environmental dimensions, including biodiversity impacts, human health, and toxicity associated with material production and construction. This broader perspective would strengthen the case for circular economy strategies and provide a more holistic view of sustainability in the residential building sector.

Future work could also incorporate dynamic MFA modeling to assess material flows and circularity potentials over time, as well as operational energy modeling to identify energy efficiency potentials at the municipal level.

6. Conclusions

This study provides a detailed assessment of residential building material stocks and their associated embodied greenhouse gas emissions at the municipal level in Norway. The analysis revealed that concrete surrogate is the most dominant material in the national building stock resulting in 139.3 Mt, while construction-grade steel contributes the most to emissions accounting for 21.8 Mt CO_2e due to its high carbon intensity. Material stocks and emissions are concentrated in the largest urban centers such as Oslo, Bergen and Trondheim, whereas per-capita emissions are highest in rural municipalities dominated by single-family homes, reaching 17 tonnes CO_2e per person. The combination of municipal-level heated floor area data with material intensities differentiated by building type and construction cohort proved to be a robust and adaptable method for high-resolution assessment. The findings could support targeted strategies for emission reduction, improved material efficiency and the implementation of circular economy practices. The interactive dashboard developed in this study facilitates exploration and communication of results, making it a practical tool for policymakers and planners. The methodological approach can be effectively applied to research in other countries, provided that comparable data is available. Future research incorporating historical and region-specific data at different temporal resolution, as well as additional environmental impact categories, will further improve understanding of building and material stock dynamics and support more informed sustainable urban development and resource management strategies.

Annexe

Table A1 Parameters for Monte Carlo simulation using triangular distribution. Abbreviation used in the Parameter column: MI – Material Inventory; HFA – Heated Floor Area; EI – Energy Intensity; CI – Carbon Intensity; GWP100 – Global Warming Potential over a 100-year horizon. The Mode represents the most likely value derived from raw data sources. The Min and Max values are calculated based on the standard deviations specified in Chapter 3 of this study

Parameter	**Mode**	**Min**	**Max**	**Unit**	**Source**
MI total: AB_1955	1043.9	730.7	1357.1	tonne	(Amini et al. 2024)
MI total: AB_1956_1970	1890.2	1512.2	2268,2		
MI total: AB_1971_1980	2442.2	2198.0	2686.4		
MI total: AB_1981_1990	2539.7	2285.7	2793.7		
MI total: AB_1991_2000	2235.1	2011.6	2458.5		
MI total: AB_2001_2010	2181.8	1963.6	2399.9		
MI total: AB_2011_2020	2520.6	2268.5	2772.7		
MI total: AB_2021	2520.6	2268.5	2772.7		
MI total: SFH_1955	190.7	133.5	247.9		
MI total: SFH_1956_1970	200.8	160.6	240.9		
MI total: SFH_1971_1980	221.4	199.3	243.5		
MI total: SFH_1981_1990	280.0	252.0	308.0		
MI total: SFH_1991_2000	133.9	120.5	147.3		
MI total: SFH_2001_2010	144.4	130.0	158.8		
MI total: SFH_2011_2020	133.2	119.9	146.5		
MI total: SFH_2021	133.2	119.9	146.5		
MI total: MFH_1955	268.0	187.6	348.4		

MI total: MFH_1956_1970	322.5	258.0	387.0		
MI total: MFH_1971_1980	328.5	295.6	361.4		
MI total: MFH_1981_1990	319.7	287.7	351.7		
MI total: MFH_1991_2000	154.0	138.6	169.4		
MI total: MFH_2001_2010	162.5	146.3	178.8		
MI total: MFH_2011_2020	207.0	186.3	227.7		
MI total: MFH_2021	207.0	186.3	227.7		
HFA: AB_1955	56.0	39.2	72.8	m²/dwelling	(Sandberg et al. 2017)
HFA: AB_1956_1970	53.0	42.4	63.6		
HFA: AB_1971_1980	61.0	54.9	67.1		
HFA: AB_1981_1990	64.0	57.6	70.4		
HFA: AB_1991_2000	58.0	52.2	63.8		
HFA: AB_2001_2010	60.0	54.0	66.0		
HFA: AB_2011_2020	68.0	61.2	74.8		
HFA: AB_2021	68.0	61.2	74.8		
HFA: SFH_1955	133.0	93.1	172.9		
HFA: SFH_1956_1970	139.0	111.2	166.8		
HFA: SFH_1971_1980	144.0	129.6	158.4		
HFA: SFH_1981_1990	161.0	144.9	177.1		
HFA: SFH_1991_2000	139.0	125.1	152.9		
HFA: SFH_2001_2010	142.0	127.8	156.2		
HFA: SFH_2011_2020	152.0	136.8	167.2		
HFA: SFH_2021	152.0	136.8	167.2		

HFA: MFH_1955	88.0	61.6	114.4		
HFA: MFH_1956_1970	101.0	80.8	121.2		
HFA: MFH_1971_1980	100.0	90.0	110.0		
HFA: MFH_1981_1990	96.0	84.6	105.6		
HFA: MFH_1991_2000	85.0	76.5	93.5		
HFA: MFH_2001_2010	88.0	79.2	96.8		
HFA: MFH_2011_2020	96.0	84.6	105.6		
HFA: MFH_2021	96.0	84.6	105.6		
Manufacturing EI total: SFH_standard	218.0	196.2	239.8	MJ/m²	ODYM-RECC (Pauliuk et al. 2021; Pauliuk 2024)
Manufacturing EI total: MFH_standard	161.6	145.4	177.8		
Manufacturing EI total: AB_standard	161.6	145.4	177.8		
CI: natural gas	0.07	0.063	0.077	kg CO_2e/MJ	
CI: diesel	0.07	0.063	0.077		
CI: gasoline	0.07	0.063	0.077		
CI: electricity	31.0	27.9	34.1	g CO_2e/kWh	(Scarlat et al. 2022)
CI: production of cement	0.8	0.7	0.9	kg CO_2e/kg	ODYM-RECC (Pauliuk et al. 2021; Pauliuk 2024)
GWP100: production of concrete, aggregates	0.0040	0.0036	0.0044		
GWP100: production of construction grade steel, primary	2.2	1.9	2.4		

GWP100: production of wood and wood products, primary	0.12	0.10	0.13		
GWP100: production of glass, primary	0.9	0.8	1.0		
GWP100: production of insulation material	1.1	1.0	1.2		(Lausselet et al. 2020)
GWP100: production of paper and cardboard, primary	0.7	0.6	0.8		ODYM-RECC (Pauliuk et al. 2021; Pauliuk 2024)

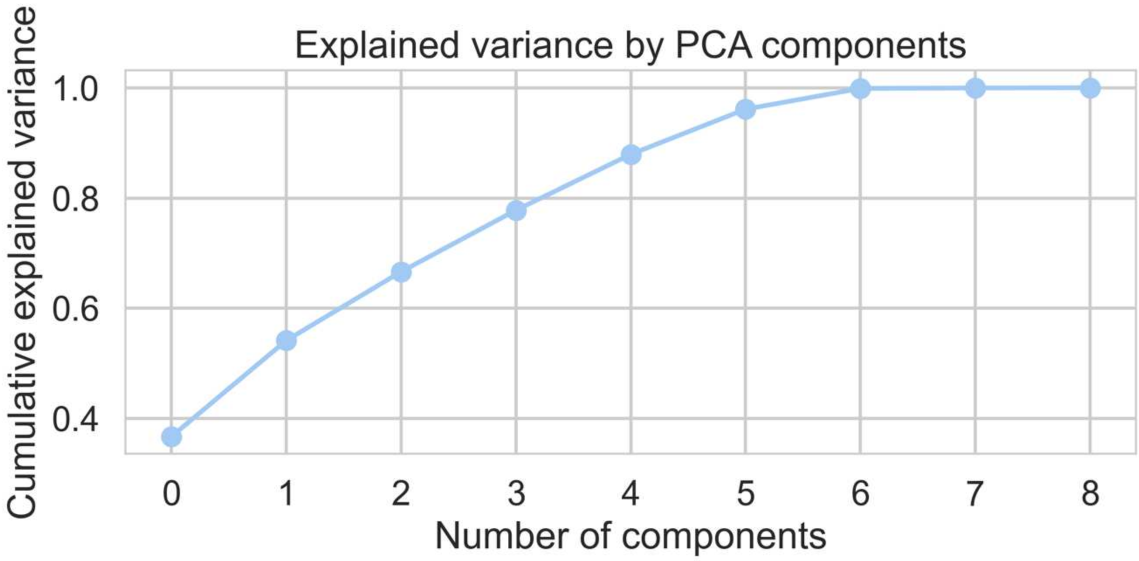


Figure A1 – Cumulative variance explained by PCA components.

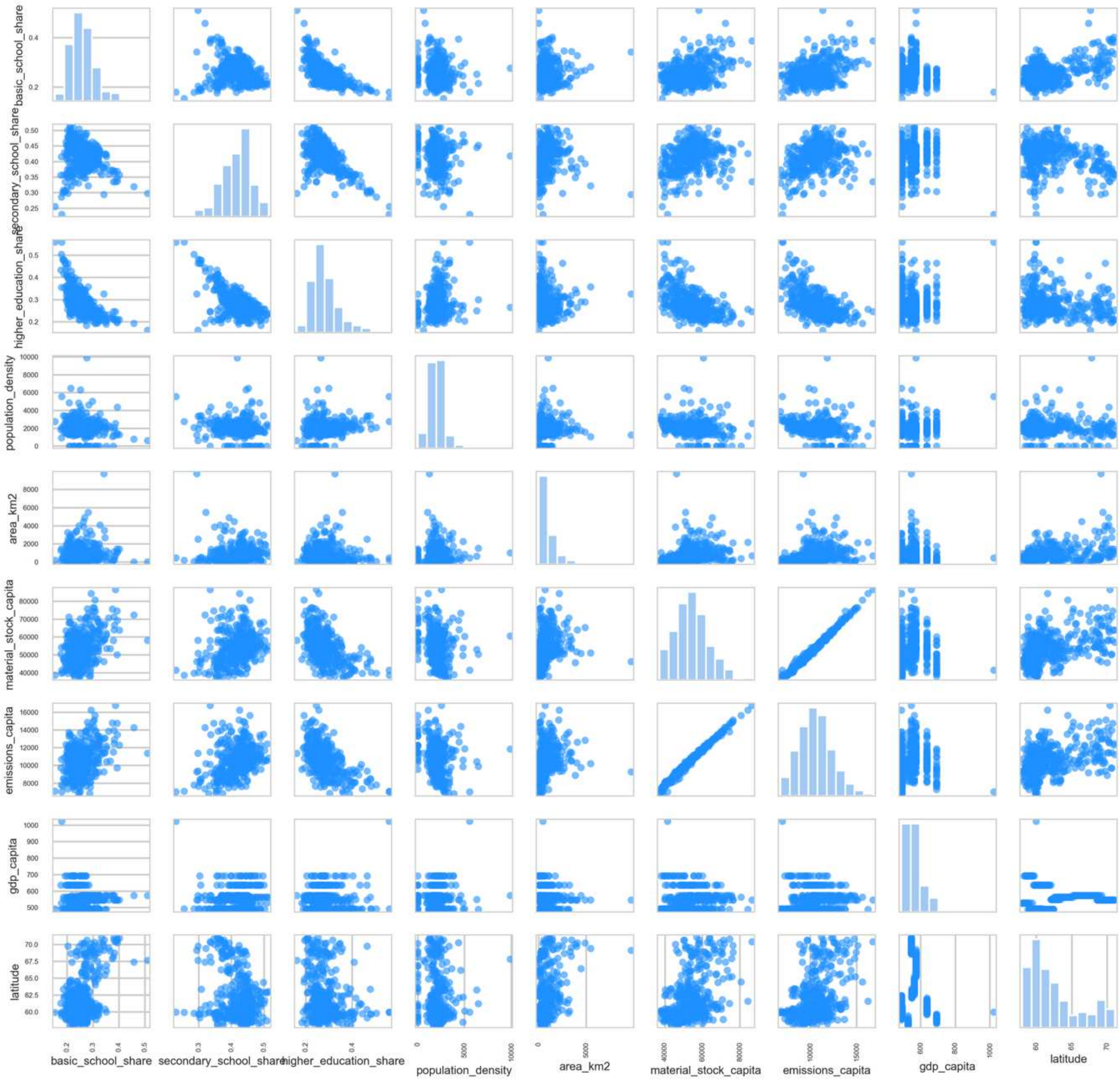


Figure A2 – Scatterplot matrix showing bivariate relationships among socioeconomic and environmental indicators.

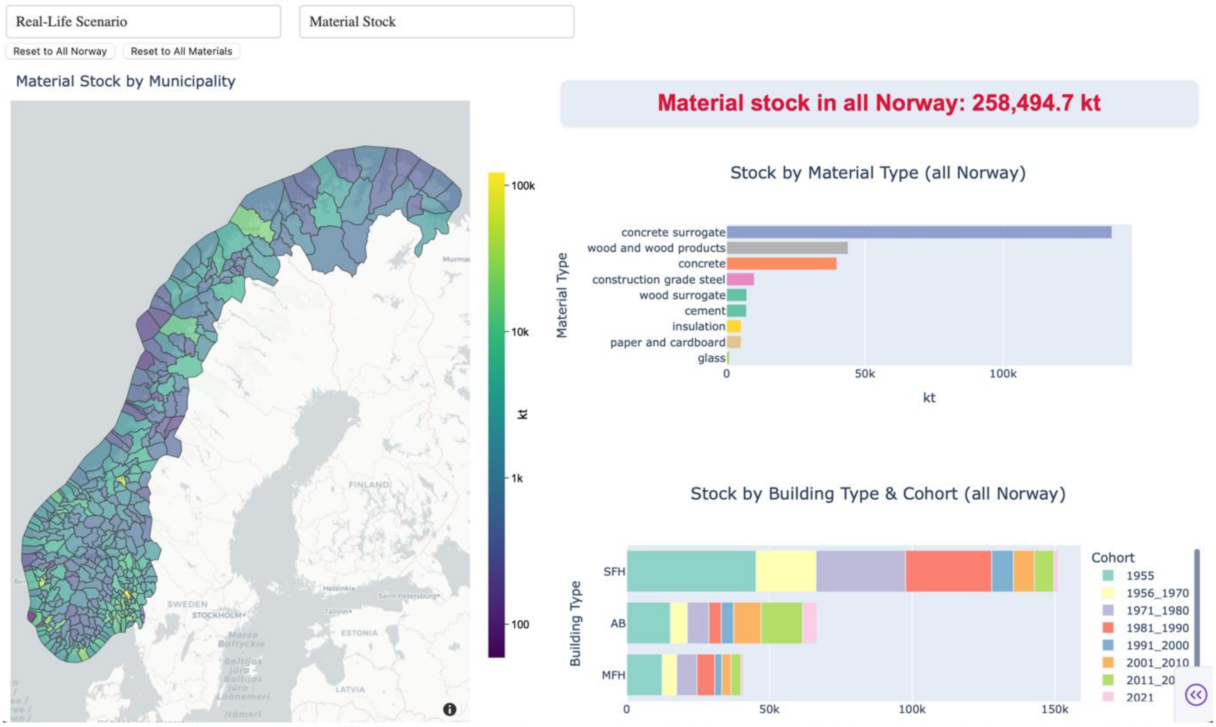


Figure A3 – Screenshot of the dashboard with the following parameters selected: Real-Life Scenario, Material Stock, all material types, all Norway.

Figure A4– Screenshot of the dashboard with the following parameters selected: Worst-Case Scenario, Manufacturing Emissions, Oslo.

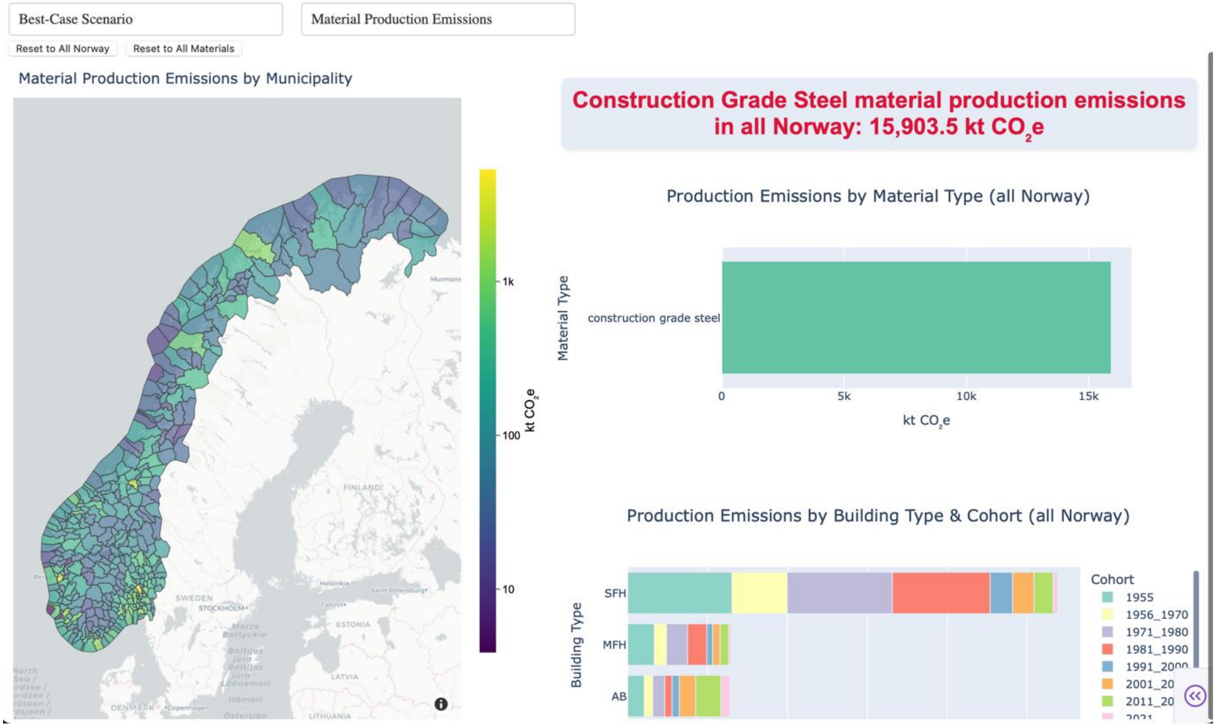


Figure A5 – Screenshot of the dashboard with the following parameters selected: Best-Life Scenario, Material Production Emissions, Construction Grade Steel material type, all Norway.

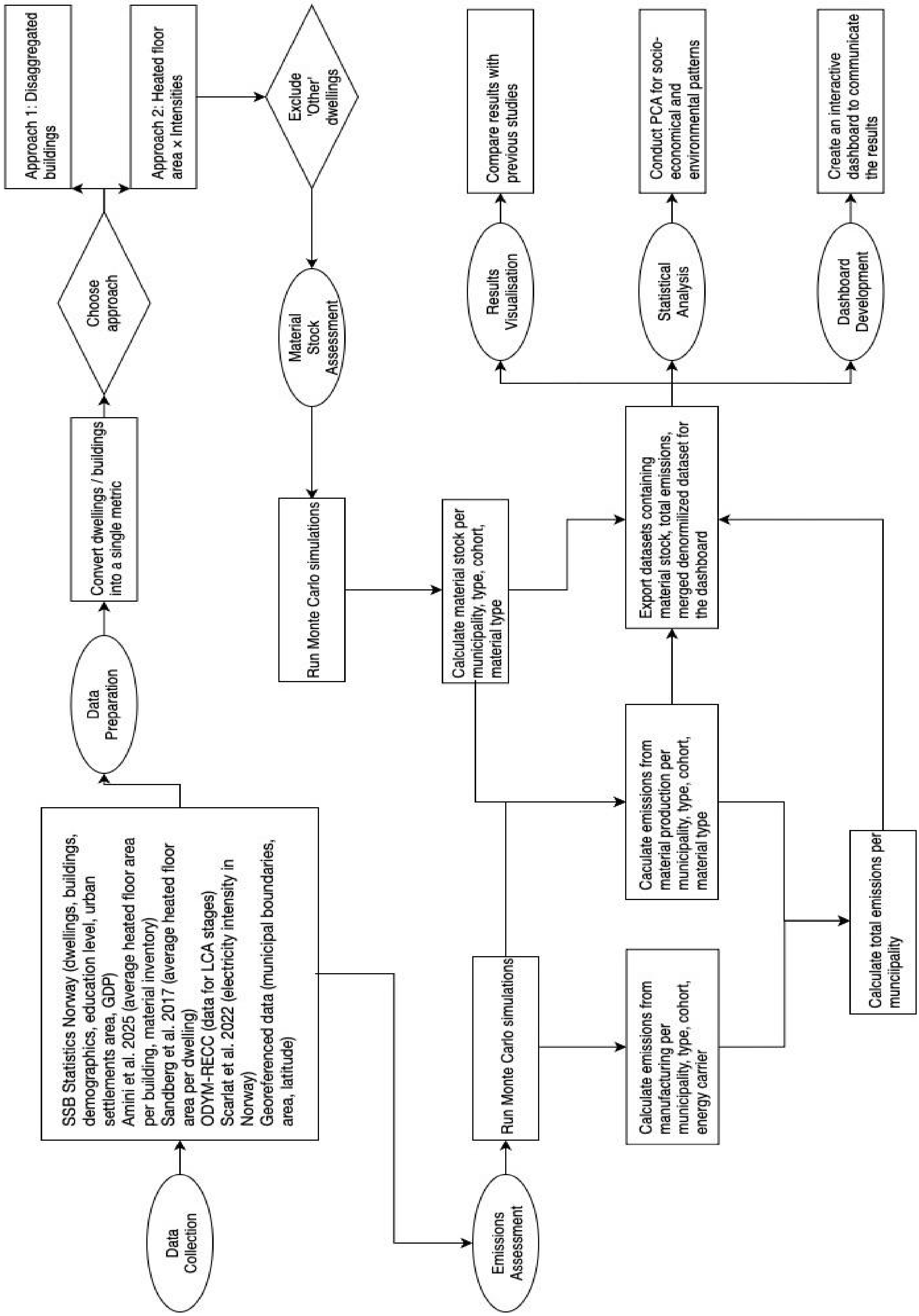


Figure A6 – The workflow schema of the analysis used in this study

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