AI Analytics for Carbon-Neutral City Planning: A Systematic Review of Applications

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Review

AI Analytics for Carbon-Neutral City Planning: A Systematic Review of Applications

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Abstract: Artificial intelligence (AI) has become a transformative force across various disciplines, including urban planning. It has unprecedented potential to address complex challenges. An essential task is to facilitate informed decision making regarding the integration of constantly evolving AI analytics into planning research and practice. This paper presents a review of how AI methods are applied in urban studies, focusing particularly on carbon neutrality planning. We highlight how AI is already being used to generate new scientific knowledge on the interactions between human activities and nature. We consider the conditions in which the advantages of AI-enabled urban studies can positively influence decision-making outcomes. We also consider the importance of interdisciplinary collaboration, responsible AI governance, and community engagement in guiding data-driven methods and suggest how AI can contribute to supporting carbon-neutrality goals.

Keywords: artificial intelligence; carbon neutral; urban planning; systematic review

Citation: Cong, C.; Page, J.; Kwak, Y.; Deal, B.; Kalantari, Z. AI Analytics for Carbon-Neutral City Planning: A Systematic Review of Applications. *Urban Sci.* **2024**, *8*, 104. https://doi.org/10.3390/urbansci8030104

Academic Editor: Luis Hernández-Callejo

Received: 31 May 2024
Revised: 23 July 2024
Accepted: 31 July 2024
Published: 1 August 2024

1. Introduction

In recent years, the pursuit of carbon neutrality has emerged as a crucial objective for cities across the globe in addressing the escalating threat of the climate crisis. Cities produce over 70% of global greenhouse gas emissions (GHGs), due to their high density and intense production and consumption activities [1]. In response, many cities worldwide have set up long-term plans to become carbon-neutral by upgrading infrastructure, improving management, optimizing operations, and transforming lifestyles towards greener urban living.

Achieving carbon neutrality in complex urban systems requires a thorough understanding of urban carbon dynamics, including identifying and accounting for both natural and human-influenced carbon exchanges and interaction effects. The inherent uncertainty and socio-technical complexity of urban environments, however, makes this task challenging, often resulting in expedient or suboptimal designs based on personal intuition and/or professional norms [2–4].

The rapid evolution of the Internet of Things (IoT), increasing use of big data, and artificial intelligence (AI) applications have enriched urban studies and planning. An explosion of research in these areas has enabled real-time data analysis, advanced predictive modeling, complex optimization routines, and adaptive decision making. For example, the number of published papers focusing on applying AI to urban planning has surged in recent years, with over 900 articles released since 2020 (according to a search for urban AND planning AND artificial AND intelligence in Scopus, 905 papers have been published since 2020). This plethora of activity in the literature has created excellent opportunities for using these emerging analytical tools to translate broad climate strategies into research and adaptation strategies at the local level. AI capabilities have been noted to help cities optimize energy usage, enhance transportation efficiency, estimate carbon emissions, and provide behavioral insights to advance their carbon neutrality goals [5–8].

Despite the promising connection between AI and carbon-neutral urban planning, questions remain regarding the specific pathways linking AI to planning research in this field. Carbon-neutral urban planning and AI are both broad concepts, allowing researchers to apply the technology, directly or indirectly, in a range of areas, including urban ecology, public health, transportation, land use, energy, and waste management [9,10]. While this flexibility is advantageous, it also leads to confusion regarding the efficacy of AI across various sectors and its role in advancing carbon neutrality objectives. Additionally, it is imperative to explore how the frequently criticized limitations and biases of AI play out in the realm of carbon neutrality planning. It is also important to consider whether the widespread use of AI in planning can be implemented in a way that is efficient and useful enough to offset the large carbon footprint currently associated with resource-intensive high-power computing [11,12] (Figure 1).

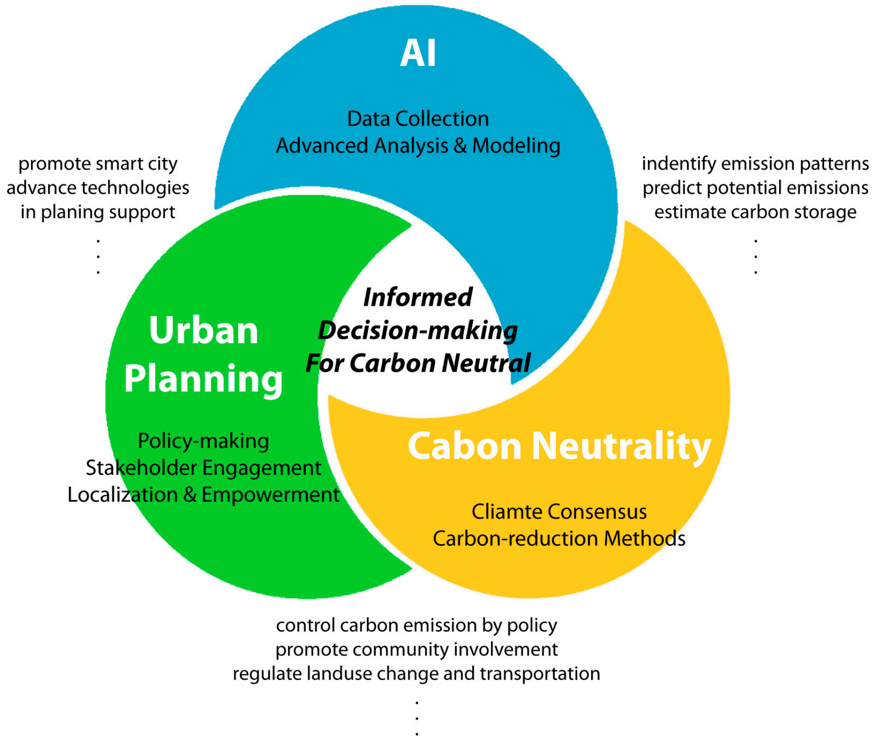

Figure 1. Relations between AI, urban planning, and carbon neutrality.

This paper aims to discover the potential synergy between carbon-neutral city development goals and the utilization of AI in urban planning. To that end, we examine three questions: (1) In what areas have planners and planning researchers used AI to advance carbon-neutral goals? (2) What topics or findings has AI contributed to carbon neutrality planning? and (3) Under what conditions can the advantages of AI-enabled planning positively influence decision-making outcomes? To answer these, we perform a systematic analysis of 62 influential papers on the use of AI in urban planning and carbon related contexts using the Systematic Reviews and Meta-Analyses (PRISMA) methodology. We discuss both the current situation and future potential of AI in urban planning by critically assessing the benefits, risks, limitations, and promise of AI methodologies.

2. Background Literature

2.1. Related Reviews

Several research papers reviewing AI for urban studies have been published recently. These reviews typically focus on how AI has been utilized and can be further applied in planning research, describing various methods and datasets. However, the scope of these reviews varies. Some provide a broad overview of the potential of AI in urban planning, while others zoom in on specific sub-fields such as climate change or urban form planning (Table 1).

Table 1. Relevant reviews in recent years.

Sources	No. of Articles Reviewed	Topics	Major Findings
[6]	91	Algorithmic urban planning for smart and sustainable development	AI application fields: (1) urban data analytics and planning decision support, (2) urban and infrastructure management, (3) urban environmental and disaster management, and (4) urban monitoring and development control.
[11]	A scoping review (1000+)	How planners interact with AI tools	A topology of urban planning using AI, from traditional planning to AI-autonomized planning.
[12]	44	AI-based solutions for climate change	Focus on automated operations: discovery, distribution, and transmission enabled through AI.
[13]	56	Using AI for climate change adaptation	Identifies AI advantages in forecasting, projection, and modeling extreme weather events, resource use, and conservation and adaptation efforts.
[14]	140	Unsupervised machine learning in urban studies	Records and summarizes the topic and techniques of unsupervised learning used in planning studies and provides insights into methods' evolution and prominent future application trends.
[15]	521	ML method for sustainable urban development	Identifies most urban planning issues for sustainability, including land use/cover, urban growth, urban buildings, urban mobility, and urban environment.

Some takeaways from our review of the literature are as follows. First, we find there is some consensus for defining AI but not for "urban planning AI". AI involves the use of mathematical models to enable computer learning without direct instruction [16]. Various terms associated with AI, such as scenario modeling, machine learning, and deep learning, all represent applications of this technology in urban-related research. Some reviews apply a broader definition of AI that includes not only algorithms used to assist urban decision making, but also automated, physical systems that facilitate urban service delivery and operations, such as traffic control with intelligent transportation systems (ITSs) and smart garbage collection systems [5,12]. In the narrower sense, others emphasize the advantages of AI-enhanced computation, highlighting its applications in forecasting and simulating extreme weather or urban growth events, for which real-world experimentation is impractical [13,15]. One recent review focuses more specifically on unsupervised machine learning in generating insights into trends and patterns of urban phenomena [14].

Second, we need to narrow down the definitions of AI and the urban planning field to examine their applications. AI has been applied in a broad range of urban study areas. These include social sensing [17], monitoring land cover change [18], screening urban trees through street-view images [19], estimating commercial and residential building energy consumption [20], automating street network generation [21], facilitating participatory governance in online education [22], natural language processing (NLP) applications for analyzing historical planning documents [23], generative AI for retrieving data and eliciting public input [24], and many others. This indicates a need to identify relevant areas for literature screening when conducting a review of AI in carbon neutrality planning, thus enabling an examination of AI possibilities that align with these.

Third, we found the literature suggests that advanced AI analytical tools to facilitate "rational planning" were inadequate for tackling complex and "wicked problems" in urban planning [25,26].

Most previous reviews focus on social complexities and application contexts. One states that AI in planning "requires strategic direction at all levels" [5], while another tackles this issue directly by delineating the transition from planner-directed AI support to self-learning systems with minimal intervention, while also anticipating governance challenges at each stage ([11], p. 3). Despite the significance of these frameworks and visions, an unanswered question remains regarding the conditions under which the benefits of AI-enabled planning positively affect decision-making outcomes. This question is the focus of our review, which also investigates the challenges of AI and their implications in the specific context of carbon neutrality planning.

Finally, in terms of the domains of these reviews, we have not found any that specifically address AI's role in carbon neutrality planning, presenting opportunities for summarizing current research findings, data, analytics, and actions.

2.2. Carbon-Neutral Approaches and Potential of AI in Planning

In this section of our review, we first note carbon reduction and carbon capture and storage/sequestration as two primary paths towards achieving carbon neutrality. These efforts span various sectors, including energy, transportation, manufacturing, and conservation [27]. Carbon reduction primarily involves altering the energy mix by transitioning from high-emission sources to greener alternatives or by curbing demand [28]. Cities can, e.g., improve energy efficiency, develop net-zero buildings, transition to cleaner energy sources, and promote sustainable consumption to reduce direct emissions. Carbon storage proactively mitigates carbon emissions by capturing CO_2 from emission sources, repurposing it for various industrial processes or securely storing it underground. Carbon sequestration typically employs ecological methods, utilizing natural or artificial reservoirs like vegetation or ocean systems to trap, store, and absorb carbon compounds, thus reducing atmospheric CO_2 concentrations [29].

In this review, "AI" refers to the application of AI algorithms within quantitative research in urban planning, rather than its broader usage in automating operational systems. Our focus lies in examining how AI is employed to construct advanced models to identify patterns and forecast trends. In this context, leveraging AI proves valuable in anticipating scenarios that may be addressed by formulating strategies to mitigate negative impacts of climate change, including reducing carbon emissions and potentially averting losses of carbon sinks wherever feasible.

The goals of carbon-neutral urban planning are focused on creating sustainable, energy-efficient, and environmentally friendly urban environments. Reviews on AI in planning indicate that AI has already been utilized to help achieve several key objectives of carbon-neutral urban planning, including reducing GHG emissions, promoting energy saving, sustainable transportation, and so on. Therefore, we map and outline how AI can contribute to advancing carbon neutrality goals as the starting point of our review (see Table 2).

Table 2. Primary carbon-neutral approaches and related AI application fields.

Research Topic	AI Pathways to Carbon Neutrality Goals
Emission control	Identify emission pattens and drivers; predict total and sectoral emissions.
Nature conservation	Estimate carbon storage capacity; anticipate carbon sink loss due to changes in land use change.
Energy saving	Model energy use of buildings; estimate heating and cooling energy consumption; evaluate energy policies.
Land use and transportation planning	Estimate emission reduction through optimizing trips, routing, and ridesharing and anticipating walking, biking, and the use of public transport.

3. Research Method

Building on our background literature review, we apply the Systematic Reviews and Meta-Analyses (PRISMA) method in an effort to improve transparency in our systematic review (Figure 2). Using the PRISMA process, we first search for articles using general terms like "urban planning" and "artificial intelligence". Based on the scoping review in the previous section, we continued to add terms including "carbon", "emission", "GHG", "carbon storage", "energy emission", and "transportation emission", as well as replacing "artificial intelligence" with more specific terms, including "machine learning" and "deep learning", for each query. We conducted the keyword search of the SCOPUS database in May 2024, under Document Search within "Article title, Abstract, Keyword".

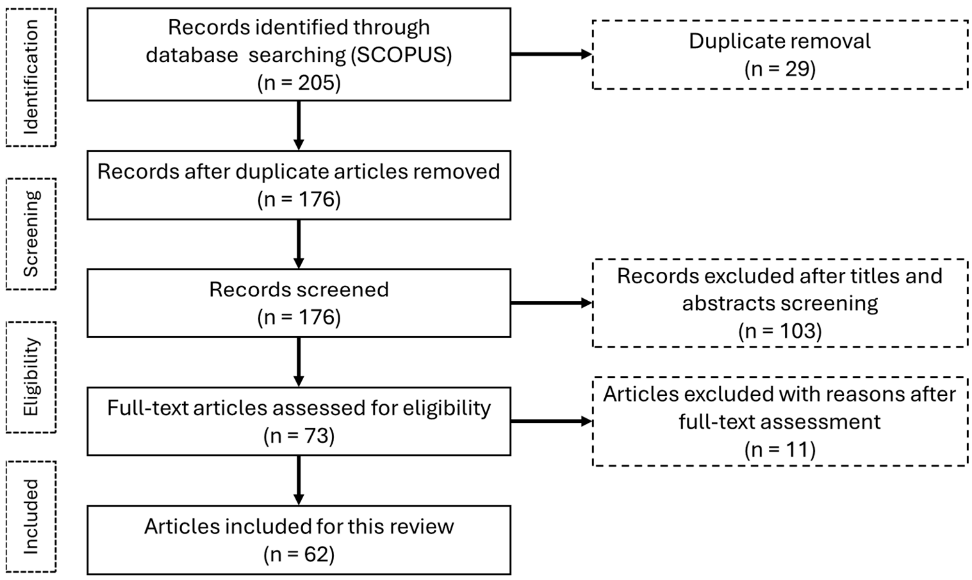

Figure 2. Flowchart of the systematic review and meta-analysis (PRISMA)-based literature review process.

Following the keyword search, we use titles and abstracts to screen each article against our study selection criteria. Our inclusion criteria are as follows: (1) articles that directly address one of our predefined paths: carbon reduction, carbon capture, and storage/sequestration; and (2) articles that are conducive to urban policy enhancement or offer insights into sustainable urban development. Our exclusion criteria are as follows: (1) studies not related to our identified paths or only tangentially related to carbon; (2) articles that do not relate to human settlements, such as those focused on oceans, shale reservoirs, or wetland rehabilitation; and (3) articles focused on the biological aspects of carbon capture technology.

Lastly, we review these articles and record the topic areas, study goals, data, AI methods, author(s), and year of publication using Zotero as the primary document-reviewing tool and Excel for data collation.

4. Result

The keyword search produced 176 articles after eliminating duplicates. Our title and abstract screening identified 73 for a full-text review. In our reading of the text, we concentrated on applications of contemporary machine learning and AI techniques, excluding process-based analyses (for example, net primary productivity (NPP) models). We also removed articles that address emissions with machine learning methods but do not align with our research intentions or urban policy objectives. Eleven were removed at this stage, and a final pool of 62 articles were finalized for a more systematic analysis.

Table A1 summarizes the characteristics of the 62 studies included in the review. All studies were published within the past five years. Fifty-eight were peer-reviewed journal papers, and four were conference papers. Their topics (categorized by summarizing common types from multiple related studies) primarily encompassed four main areas: emission prediction, energy consumption estimation, carbon storage and sequestration, and land use change and emission response.

The studies in the final dataset employed AI methods for diverse purposes. In delineating the primary objectives of utilizing AI applications, we found that prediction and factor analyses represented the predominant aim of these research efforts. Prediction involves leveraging machine learning techniques to construct predictive models and forecast outcomes. Factor analysis entails deciphering influential factors within these prediction models. Other objectives included clustering, classification, and optimization.

The urban data sources identified in our review primarily consisted of numerical data (such as census and survey data with numerical attributes), image data (including satellite and street view imagery), spatial data (such as points of interest, building footprints, land use/land cover (LULC) information, night-time lights, LiDAR point clouds, and GPS trajectory data), and multi-source data covering two or more of these types.

The majority of the studies reviewed employed machine learning and deep learning techniques. Specifically, in machine learning, they utilized algorithms such as Random Forest (RF), Gradient Boosted Decision Trees (GBDT), Extreme Gradient Boosting (XGB), Support Vector Machines (SVMs), k-Nearest Neighbors (kNNs), and Artificial Neural Networks (ANNs) for tasks such as clustering and prediction. Machine learning approaches are promising alternatives to conventional statistical methods such as generalized least squares (GLS) [30], demonstrate a high performance in classifying geospatial datasets assessed by the area under the ROC curve (AUC) [31], and can be successfully applied to a wide variety of urban data [14]. SHAP (SHapley Additive exPlanations) interpretations of measuring the relative contribution of each variable played a significant role in the studies involving factor analyses [20,32,33].

Studies in the realm of deep learning mainly used Back Propagation Neural Networks (BPNNs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) for analyses dealing with images [19], unstructured text data [23], and time-series data [34]. Urban phenomena typically encompass intricate topographies and temporal dynamics. Deep Neural Networks (DNNs) possess an added advantage over conventional machine learning methods due to their potential to effectively handle such complex scenarios. Their inherent nonlinear fitting properties make them well suited for navigating the intricacies of urban environments, a capability that has led to their widespread application across various industries.

In Figure 3, we extract the core features that characterize each study (topic, goal, and data type used) and show the overlap and relationships between feature segments. Predicting emissions is a prevalent practice in academic papers. Some papers within this field not only focus on estimating emission numbers, but also delve into identifying the underlying factors contributing to these predictions, driven by a desire to uncover the mechanisms behind black-box learning models to offer more transparency and identify decision-making implications.

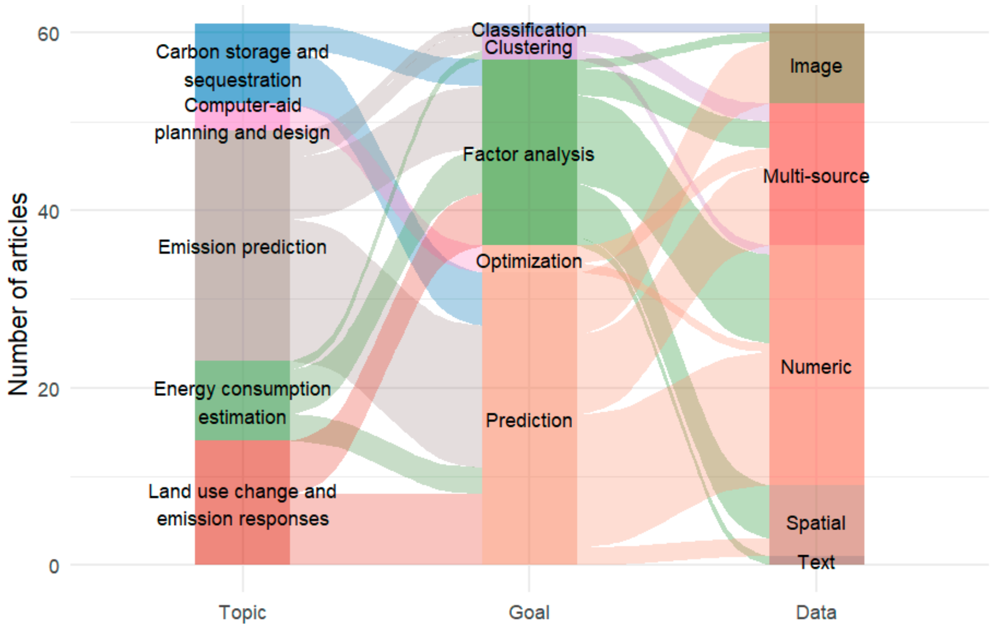

Figure 3. Topics, applications, and data type segment covered in the selected dataset (n = 62 articles).

4.1. Topic Review

4.1.1. Emission Prediction

Forecasting emissions is crucial for carbon neutrality planning, as it provides insights into future emission levels and guides preparation efforts. AI methods are particularly advantageous for the estimation of emissions, owing to their capacity to handle large and complex datasets while discerning intricate patterns. Estimates can be made based on historical emissions data [35–37], sensor data [38], and street view images [39]. Sector-specific predictions, such as those focusing on emissions from transportation [40], commercial retail [41], and building and construction [42], were also prevalent in the selected literature.

A recurring related area of study was exploring the connection between urban infrastructure and emissions. This explains the increasing use of explainable AI, which helps unravel the factors driving emissions. Studies in this domain often identified the following: (1) the dominant features of certain types of emissions, which help decision makers determine the main direction of carbon reductions, and (2) the threshold value for each feature, which helps them check which configuration of features is not justified and target carbon reduction policies. The studies usually applied a combination of XGB and SHAP for this task, e.g., to quantify the heterogeneous impacts of the urban built environment on traffic carbon emissions [8], investigate how urban morphological and building geometry affect building energy consumption and associated GHG emissions [32], and identify location-specific relevance of the built environment for urban motorized travel [33]. The observed threshold effects of induced CO_2 emissions indicated that low-carbon policies should be tailored to densifying urban cores and relieving peripheral low-income communities from dependence on cars.

Many studies used multiple machine learning algorithms to train models, thereby allowing comparisons of different approaches [43,44]. In terms of methodology, this approach helps find a balance between prediction accuracy and the prevention of overfitting. For the purpose of emission prediction, it sheds light on the strengths and limitations of different modeling techniques, indicating the algorithms best suited for specific emission prediction tasks.

4.1.2. Carbon Storage and Sequestration

Quantifying carbon storage and sequestration is necessary to understand the amount of CO_2 captured and retained by various ecosystems, which helps assess human impact on the environment and develop effective carbon management strategies [45]. Conventional estimation methods typically rely on the quantification of aboveground biomass (AGB), but integrating remote sensing with field-based methods offers cost-effectiveness and spatial precision. Since the 1990s, fine-resolution remote sensing has been employed to gauge carbon storage and sequestration in urban forests, often in conjunction with ground observations and modeling efforts [46,47]. Regression analyses, including linear, multiple, and exponential forms, have been employed to predict forest biomass.

AI-based algorithms have been proposed to better capture the spatial and temporal variation in carbon storage and sequestration. Conventional parametric methods, which assume data to be a function of a fixed number of parameters, often fail to capture non-linear relationships accurately. In contrast, machine-learning-based approaches, such as kNNs, SVMs, RF, and XGBoost, adapt the number of parameters based on the training sample size. This flexibility is advantageous as it does not impose restrictions on the variable type or distribution of predictor variables, allowing for a more comprehensive exploration of the relationship between response and predictor variables [48]. This typically yields a higher prediction accuracy [49,50]. Studies in this category in our review covered carbon capture process simulation and capture capacity prediction [51,52], the carbon storage estimation of forests, wetlands, and other ecosystems [53,54], improving a model of carbon storage capacity estimation [55], a scenario simulation of land use change and carbon storage response [42,56,57], and carbon decision support tools [58].

4.1.3. Land Use Change and Emission Response

Previous studies on urbanization and climate change have revealed a trend for urban growth to lead to heightened GHG emissions and a concurrent decline in carbon sequestration capacity due to changes in land use, resulting in substantial net increases in GHG emissions in certain regions [59,60]. Models offer insights into the environmental consequences of land use change and aid in making informed decisions in regional land use planning, aiming to curb emission increases and safeguard vital ecosystems [61–63].

Conventional cellular automata (CA)-based land use simulation can be considered a form of machine learning, albeit in a specific sense. Machine learning broadly refers to algorithms that enable computers to learn patterns and make predictions from data without being explicitly programmed. While CA-based simulations typically apply pre-defined rules, the simulation process involves iterative adjustments based on observed patterns and outcomes. This process can be seen as a form of "learning" from the simulation results to refine the model and improve its predictive accuracy.

AI can enhance land use simulation in multiple ways. One notable approach involves employing reinforcement learning or genetic algorithms to automatically learn or refine the rules governing land use change. For example, one study used land use types of pixels that experienced increases during a specific period, along with driving factors for land use expansion, to train an RF classification model [64]. Spatially explicit modeling, as highlighted in another study [65], can be particularly beneficial for pinpointing development zones where emission reductions should be prioritized. A recent study improved LULC classification using a CNN, leveraging deep learning for the dynamic pixel-wise detection of LULC changes across a study area [34]. Other studies have found that AI can contribute to more effective climate and land use change modeling by integrating various social and ecological system dynamics and feedback loops [66–68].

4.1.4. Energy Consumption and Emission

Understanding energy consumption can help to guide carbon reduction policies, because it reveals where resources are used inefficiently, enabling targeted improvements and promoting the adoption of renewable energy sources. Building energy estimation is an important task since it helps in assessing the overall energy footprint of a locality or urban area. In this field, constructing a physics-based model for one building is a common approach, but can be quite time-intensive [69]. In addition to using physics-based simulation techniques, researchers are exploring data-driven methods to model annual energy consumption at the building level [70,71].

AI models are typically capable of capturing complex relationships and patterns within data [72]. This ability enables them to uncover correlations between urban structure and energy consumption [73], as well as perform long-term forecasting [74]. One study in our dataset utilized a data fusion approach to construct reliable urban building energy models, achieving an impressive 95% classification accuracy using machine learning techniques [6]. Others elucidated detailed spatial and temporal energy usage patterns using supervised machine learning algorithms [69] and developed an electric vehicle (EV) energy consumption estimation technique that accurately predicts consumption despite limited EV data and irregular driving trajectories [75]. The latter method leverages RNNs to handle temporal dependencies effectively.

4.2. Areas in Which AI Analytics Can Support Carbon Neutrality Planning

Numerous studies in our review highlighted the capability of AI in supporting carbon neutrality planning. They are listed as follows according to topic areas:

Predictive modeling: Predictive AI can enhance forecasts of future carbon emissions and energy demand, helping planners anticipate challenges and develop proactive carbon reduction strategies. Human activities affect ecosystem services in complex, non-linear ways, meaning the impact on carbon emissions varies in direction and magnitude as activities increase. Using nonparametric AI prediction methods to analyze these interactions often yields better models, providing planners with effective tools for ecosystem management and the early detection of contributing factors.

Data-driven emission analysis: AI analytics can process vast amounts of data from various sources, such as sensors, satellite imagery, open data, and government databases, to identify patterns and trends related to carbon emissions and energy consumption in cities. For instance, quantifying the impact of urban form on carbon emissions from transportation can be a complex task, and automated support is essential to streamline the process [7,36]. Data visualization techniques can aid in the presentation of data in a clear and meaningful manner, making it easier to comprehend and identify trends [20,34,76].

Decision support: Planning for carbon neutrality is predominantly influenced by the growing complexities and uncertainties inherent in the task. AI methods have proven particularly beneficial in this regard, particularly in estimating emissions, as researchers can generate various development scenarios, foresee uncertainties, and evaluate the associated consequences for each development trajectory [77]. Multiple research projects have compared the outcomes of policies and initiatives to offer recommendations (see [56,57]). This enables decision makers to devise planning responses with greater confidence and effectiveness.

Optimize solutions: AI optimization algorithms can identify the most efficient ways to reduce carbon emissions by optimizing transportation routes, energy distribution networks, and building design [78,79]. To overcome the constraint of single-objective optimization, both network complexity and prediction accuracy can be used as optimization objectives, enhancing the predictive performance of neural networks through multi-objective optimization [76]. To further enhance the efficiency of AI algorithms, ongoing efforts are being made to minimize the training requirements of deep learning algorithms [80]. This can be achieved by accelerating iterations through more efficient parallel algorithms and employing optimization techniques to reduce the number of iterations needed.

4.3. Cases Where AI Analytics May Have Limitations or Encounter Issues

4.3.1. Technical and Computational Challenges

Data quality and availability: The robustness of AI models hinges on the quality and availability of data. Multiple studies have noted issues such as poor data quality, incomplete datasets, or biases and how they can compromise the accuracy and reliability of AI analytics, resulting in flawed insights and recommendations. For instance, the absence of validated data is a recurring topic in various papers. Moreover, the accuracy of data sources significantly impacts the reliability of AI analytics [6,44,66,69,81]. Acquiring more detailed data, such as the neighborhood context, building geometry, or smart meter data from individual buildings, can often prove challenging or expensive [69].

Limitations in generating behavioral insights: AI can analyze large amounts of data related to human behavior, such as traffic and energy use, to reveal patterns and needs, thereby facilitating the design of interventions and incentives to foster sustainable practices. While a subset of the articles in our dataset addressed this aspect [32,82], it is worth noting that their explorations were predominantly data-driven. Some researchers emphasize the necessity for increased focus on "mechanism experiments" to better understand the mediators and underlying psychological determinants of policy outcomes [83]. Others suggest gaining deeper insights into individual and household decision-making processes to ascertain whether sustainable energy use results from behavior change [84]. Therefore, on top of AI analysis of behavior patterns, more knowledge is needed about the conditions determining the effectiveness of policy interventions.

4.3.2. Ethical and Societal Challenges

Ethical and equity considerations: AI analytics may exacerbate existing inequalities or biases if not carefully designed and implemented [85,86]. For example, predictive models used in resource allocation decisions may disproportionately benefit certain groups or disadvantage marginalized communities [87]. When derived from biased training data, such assumptions can reinforce inequalities in resource allocation and worsen environmental disparities [88]. Diversifying training datasets and applying bias detection and correction techniques can mitigate the effects of such discrimination.

Model opacity and validation: Planners and the public may hesitate to trust machine-generated results, especially amidst ever-changing political, economic, and environmental conditions [89]. This extends beyond AI to encompass pre-existing planning support systems (PSSs) and general software/technology challenges in planning. Advanced AI models such as DNNs are often perceived as black boxes, due to their lack of transparency in generating results. This opacity can undermine people's confidence in and acceptance of smart city systems, particularly in situations involving crucial decisions. To mitigate these concerns, researchers should actively engage with planners and community members through in-person meetings and focus groups to enhance equity and fairness in urban planning AI [90]. Researchers can also provide training and education programs to community members and stakeholders to help them understand and navigate AI planning tools and interfaces.

Emissions from AI: A number of researchers are concerned about the carbon footprint of AI itself, deriving from the energy consumption and associated GHG emissions generated during the development, deployment, and operation of AI [80,91,92]. This footprint encompasses various stages, from manufacturing hardware components to running algorithms on data centers. The high-performance computing demands of AI models, particularly deep learning algorithms, contribute significantly to energy consumption, so it is reasonable to express concern about the rapid and widespread development of AI. Optimizing computing tasks in data centers, whether by speeding up iterations or reducing their number, can be crucial in minimizing power consumption in AI [80].

4.3.3. Governance Challenges

One study in our dataset delved into the challenge of AI governance by exploring the varying levels of autonomy among AI agents involved in urban planning and charting the progression of AI in this field, advancing from AI-assisted and AI-augmented planning to AI-automated and ultimately AI-autonomized planning [11]. However, the authors point out that planning inherently entails values, judgment, and interaction with diverse stakeholders and decision makers in society, which are functions that AI agents may never fully execute.

In terms of carbon neutrality planning, planners will continue to be essential for providing deep insights into city functions [93], understanding residents' carbon footprint, and ensuring the equitable distribution of sustainable policies. While AI agents handle technical aspects like optimizing energy-efficient building designs or forecasting renewable energy integration, planners address nuanced issues such as the social equity of carbon pricing policies and the cultural acceptance of renewable energy. Learning from both successful and unsuccessful examples helps local governments enhance their planning capabilities and address AI's limitations in urban policymaking and planning.

5. Discussion

In this study, we examine three research questions. Our first two were carefully considered in previous sections: (1) In what areas have planners and planning researchers used AI to advance carbon-neutral goals? and (2) What topics or findings has AI contributed to carbon-neutral planning? Our final question is discussed at length below: (3) Under what conditions can the advantages of AI-enabled planning positively influence decision-making outcomes?

5.1. Conditions in Which AI Analytics Can Support Carbon Neutrality Planning

Through our review, we identified favorable conditions for AI analytics to support carbon neutrality planning. Many of these conditions are not specifically tailored to carbon, but can be applied to other areas, because the use of AI can be seen as an extension of longstanding discussions on PSSs, the role of technology, and expertise. Many of these uses, benefits, and challenges existed before AI, but they have gained renewed significance with the widespread adoption of AI across disciplines and the growing societal impact of carbon emissions. Below, we explore the intersection of AI and carbon neutrality, occasionally revisiting some previously discussed concepts in this specific context.

Access to data: In the context of carbon neutrality planning, having access to high-quality, comprehensive data on carbon emissions, energy consumption, urban infrastructure, and demographics is essential for AI training methods. This condition is advantageous for areas with abundant data but may not be favorable for places with limited data availability. In such cases, techniques such as transfer learning become valuable, allowing knowledge from one task or domain to be applied to another, particularly in areas with sparse data resources [75].

Integration with decision-making processes: Integration ensures that AI recommendations are not just theoretical but are translated into concrete actions that can address real-world challenges effectively. AI results gain meaning if interpreted within a context. In a carbon-neutral context, for instance, knowing where ecoservices benefit us the most helps us decide where to implement them [94,95]. For urban planners, the utilization of AI should not be driven solely by novelty or popularity, but rather directed towards its strategic application as a tool for addressing specific purposes and decision-making tasks.

Stakeholder engagement: Collaboration and engagement with various stakeholders, including government agencies, businesses, community groups, and residents, are crucial for the successful implementation of AI-driven carbon neutrality planning initiatives [96,97]. One reason is that laboratory simulation results often fail to consider the diverse array of social, economic, and environmental factors prevailing in real-life contexts [21]. Input from stakeholders and local knowledge across various regions and dimensions can significantly influence low-carbon development outcomes and broader planning objectives. Moreover, stakeholder engagement helps the public accept and use AI initiatives. This mutually beneficial process enhances technological advances, builds trust, and increases the adoption of new technology.

To achieve better stakeholder engagement, governments must first commit to openness and cooperation. Whether local governments actively seek feedback from citizens and collaborate with private stakeholders significantly impacts how users respond to participation opportunities [98]. One study in our dataset found that government-led online surveys on carbon emissions had limited impact if the government (1) focused narrowly on disseminating information rather than genuinely promoting active citizen participation, or (2) took no actions in regards to or provided no responses to the feedback received [99]. In conventional participation settings, there is often limited time for the public to digest information and discuss issues [100,101]. Therefore, AI-generated information must be properly communicated to facilitate meaningful engagement.

Planners should also seek and foster intrinsic motivation from the public [99]. Research on technology-based participation approaches shows that residents are most likely to become involved in decision making when the decisions directly affect their lives [102] and benefit their community [103,104]. Planners and researchers should ensure that participants understand the relevance of the issues to the public. This means aligning the use of AI technology and new data with community interests, rather than planning- and government-dominated agendas [105,106].

Integrate disciplinary knowledge: An interdisciplinary process can significantly support policymaking through sharing data, exchanging knowledge, and crafting integrated and cost-effective interventions. While AI is rooted in computer science, when used in a climate planning context, its application should align with planning values, rather than solely pursuing optimization. The complexity of policy landscapes often exceeds the capabilities of straightforward computational solutions, necessitating a holistic approach that considers not only technical aspects, but also intricate social dynamics.

Furthermore, domain knowledge enhances the usability of AI. Carbon neutrality planning inherently spans multiple disciplines, requiring collaborative knowledge exchange between social scientists and policymakers to yield comprehensive policy insights [5]. For instance, integrating energy usage data with behavior change research enables targeted campaigns for energy-efficient practices [107].

5.2. Theory and Practice Gap

The literature on AI-driven urban planning primarily explores theoretical advances, offering model comparisons and proposing new approaches. However, a noticeable disparity between theory and practice in the sector persists. The role of computation in informed decision making has long been a topic of discussion in planning, as has the gap between the availability of PSSs and their uptake in practice [108]. This challenge is further exacerbated by public apprehension about the impacts of AI [109].

Collaborative planning, which involves stakeholders and multiple disciplines, is crucial for supplementing laboratory-based calculations. In the realm of carbon neutrality planning, practical insights have been gained from data-driven research on IoT-based, eco-friendly, and sustainable cities, emphasizing the importance of concerted efforts from researchers, funding bodies, policymakers, and industry professionals to advance both theoretical and empirical research in this field.

The complexity of policy landscapes often pushes the boundaries of what straightforward computational solutions can handle, thus requiring a more holistic approach that does not focus solely on technical problems, but also takes into account the intricate social dynamics at play. Consequently, future planning education needs to shift its focus to the integration of computational problem solving with a deep understanding of social contexts.

An important consideration at this stage is the readiness of planners to embrace and effectively use emerging AI technologies within the realm of carbon neutrality planning. This involves two aspects: (1) the current and prospective ability of AI to cater for the requirements of planners, and (2) the willingness and capacity of planners to adopt and harness technology. The literature provides insights into the former factor, while the latter will evolve over time with observations of the adoption of technologies by planners.

Research suggests that barriers to the uptake of computational PSSs in practice can be at least partly overcome through user involvement in the development of these technologies, which could be a helpful insight for the developers of AI-based planning tools [90,108]. Ultimately, the extent of planners' awareness and knowledge about AI will significantly influence the uptake of these technologies within the profession.

6. Conclusions

This review offers urban planning researchers interested in carbon-neutral planning a comprehensive overview of AI-driven analyses and their applications. Our review attempts to assess how planners and planning researchers have utilized AI to advance carbon-neutral goals and what topics or findings AI has contributed to carbon-neutral planning. Through an analysis of 62 papers, we present thematic findings, including goals, research topics, data modalities, and corresponding models or algorithms. Finally, we evaluate the conditions under which AI-enabled planning can positively influence decision-making outcomes.

Our review highlights the achievements of AI in supporting time-consuming tasks in model prediction, carbon storage, emission estimation, and energy consumption. The issues identified include gaps in connecting carbon research and actions, advanced models lacking available data, and discrepancies between data-driven approaches and behavioral insights. We also identified favorable conditions in which AI analytics can aid carbon neutrality planning and noted the importance of collaborative planning involving stakeholders and multiple disciplines as crucial complements to laboratory-based calculations. Overall, this review indicates potential for creating synergies among data, analytics, and carbon-neutral actions to support sustainable urban planning and climate goals.

When considering these insights, we note the following study limitations: (1) The chosen search keywords may have resulted in the omission of some works in the literature due to the focus on Scopus databases and an unintentional selection bias; (2) The review did not include grey literature, which often reports the latest technological developments and industry practices; and (3) Urban planning is an extensive field, so the study might not have captured all experiences and perspectives related to this research. Future research on this topic should continue to investigate how AI is utilized in planning practices and to explore opportunities for effective AI applications throughout the profession.

Author Contributions: C.C.: writing—original draft preparation, conceptualization, data curation, methodology, software; J.P.: resources, writing—reviewing and editing, validation and investigation; Y.K.: writing—original draft preparation, visualization, writing—reviewing and editing; B.D.: supervision, writing—reviewing and editing; Z.K.: supervision, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. List of publications reviewed (n = 62) and summary of review results.

Title	Topic	Goal	Data	Category	Source Ref. Number
Carbon stock inversion study of a carbon peaking pilot urban combining machine learning and Landsat images	Carbon storage and sequestration	Factor analysis	Image	Machine learning	[43]
Estimating the forest carbon storage of Chongming Eco-Island, China, using multisource remotely sensed data	Carbon storage and sequestration	Prediction	Image	Machine learning	[53]
Quantification of carbon sequestration by urban forest using Landsat 8 OLI and machine learning algorithms in Jodhpur, India	Carbon storage and sequestration	Prediction	Image	Machine learning	[110]
Two-step carbon storage estimation in urban human settlements using airborne LiDAR and Sentinel-2 data based on machine learning	Carbon storage and sequestration	Prediction	Image	Machine learning	[111]
Multi-scenario simulation of carbon budget balance in arid and semi-arid regions	Carbon storage and sequestration	Prediction	Multi-source	Deep learning (CNN-LSTM)	[68]
A spatio-temporal neural network learning system for estimating city-scale carbon storage capacity	Carbon storage and sequestration	Prediction	Multi-source	Recurrent neural network	[55]
Estimation of aboveground carbon density of forests using deep learning and multisource remote sensing	Carbon storage and sequestration	Prediction	Multi-source	Convolutional neural networks	[112]
Identifying drivers of county-level industrial carbon intensity by a generic machine learning framework	Carbon storage and sequestration	Factor analysis	Numerical	Machine learning	[44]

Table A1. *Cont.*

Title	Topic	Goal	Data	Category	Source Ref. Number
The impact of green innovation on carbon reduction efficiency in China: Evidence from machine learning validation	Carbon storage and sequestration	Factor analysis	Spatial	Machine learning	[30]
Energy-driven intelligent generative urban design based on deep reinforcement learning method with a nested Deep Q-R network	Computer-aid planning and design	Optimization	Multi-source	Deep reinforcement learning	[113]
A machine learning approach to mapping suitable areas for forest vegetation in the eThekwini Municipality	Computer-aid planning and design	Optimization	Multi-source	GIS, light gradient boosting, artificial neural networks	[31]
Multi-objective optimization of urban environmental system design using machine learning	Computer-aid planning and design	Optimization	Numerical	Gaussian process regression	[78]
Challenges for computer vision as a tool for screening urban trees through street-view images	Emission prediction	Classification	Image	Convolutional neural networks	[19]
Predicting neighborhood-level residential carbon emissions from street view images using computer vision and machine learning	Emission prediction	Prediction	Image	Machine learning	[39]
Retail commercial space clustering based on post-carbon era context: A case study of Shanghai	Emission prediction	Clustering	Multi-source	Machine learning	[41]
Illustrating the nonlinear effects of urban form factors on transportation carbon emissions based on gradient boosting decision trees	Emission prediction	Factor analysis	Multi-source	Gradient boosting decision trees	[7]

Table A1. *Cont.*

Title	Topic	Goal	Data	Category	Source Ref. Number
GIS-enabled digital twin system for sustainable evaluation of carbon emissions: A case study of Jeonju city, south Korea	Emission prediction	Factor analysis	Multi-source	GIS, back-propagation neural network	[36]
Towards low-carbon cities: A machine learning method for predicting urban blocks carbon emissions based on built environment factors in Changxing City, China	Emission prediction	Prediction	Multi-source	Back-propagation neural network	[114]
Efficiency assessment of public transport vehicles using machine learning and non-parametric models	Emission prediction	Clustering	Numerical	Fuzzy clustering	[115]
Quantifying the heterogeneous impacts of the urban built environment on traffic carbon emissions: New insights from machine learning techniques	Emission prediction	Factor analysis	Numerical	Machine learning	[8]
Peeking inside the black-box: Explainable machine learning applied to household transportation energy	Emission prediction	Factor analysis	Numerical	Neural networks	[116]
Identification of on-road vehicle CO_2 emission pattern in China: A study based on a high-resolution emission inventory	Emission prediction	Factor analysis	Numerical	Machine learning	[35]
Generic above-ground biomass estimator for urban forests using machine learning	Emission prediction	Prediction	Numerical	Machine learning	[117]
IoT-driven multi-source sensor emission monitoring and forecasting using multi-source sensor integration with reduced noise series decomposition	Emission prediction	Prediction	Numerical	Recurrent neural networks, long short-term memory	[38]

Table A1. *Cont.*

Title	Topic	Goal	Data	Category	Source Ref. Number
Carbon emission causal discovery and multi-step forecasting for global cities	Emission prediction	Prediction	Numerical	Reinforce learning	[37]
Machine learning predictions for carbon monoxide levels in urban environments	Emission prediction	Prediction	Numerical	Artificial Neural Networks	[118]
Predictive modeling of energy-related greenhouse gas emissions in Ghana towards a net-zero future	Emission prediction	Prediction	Numerical	Machine learning	[119]
Can China achieve its 2030 carbon emissions commitment? Scenario analysis based on an improved general regression neural network	Emission prediction	Prediction	Numerical	General regression neural network	[120]
Carbontracker: Tracking and predicting the carbon footprint of training deep learning models	Emission prediction	Prediction	Numerical	Convolutionalneural networks	[121]
Forecasting air transportation demand and its impacts on energy and emission	Emission prediction	Prediction	Numerical	Artificial neural networks	[122]
Assessment and regression of carbon emissions from the building and construction sector in China: A provincial study using machine learning	Emission prediction	Prediction	Numerical	Machine learning	[42]
Machine learning based estimation of urban on-road CO_2 concentration in Seoul	Emission prediction	Prediction	Numerical	Machine learning	[123]
Forecast energy demand, CO_2 emissions and energy resource impacts for the transportation sector	Emission prediction	Prediction	Numerical	Machine learning	[40]

Table A1. *Cont.*

Title	Topic	Goal	Data	Category	Source Ref. Number
An interpretable forecasting framework for energy and CO_2 emissions	Emission prediction	Prediction	Numerical	Machine learning	[124]
Modelling of CO_2 emission prediction for dynamic vehicle travel behavior using ensemble machine learning technique	Emission prediction	Prediction	Numerical	Gradient boosting regression	[82]
Analyzing the impact of three-dimensional building structure on CO_2 emissions based on random forest regression	Emission prediction	Factor analysis	Spatial	Machine learning	[81]
A novel approach for predicting anthropogenic CO_2 emissions using machine learning based on clustering of the CO_2 concentration	Emission prediction	Prediction	Spatial	Gradient-boosted decision trees	[125]
Industrial carbon emission efficiency prediction and carbon emission reduction strategies based on multi-objective particle swarm optimization-backpropagation: A perspective from regional clustering	Emission prediction	Prediction	Spatial	Back-propagation neural network	[76]
The power of attention: Government climate-risk attention and agricultural-land carbon emissions	Emission prediction	Factor analysis	Text	Natural language processing	[23]
Developing urban building energy models for Shanghai City with multi-source open data	Energy consumption estimation	Clustering	Multi-source	Machine learning	[6]
Data-driven estimation of building energy and GHG emissions using explainable artificial intelligence	Energy consumption estimation	Factor analysis	Multi-source	Light gradient boosting machine	[32]

Table A1. *Cont.*

Title	Topic	Goal	Data	Category	Source Ref. Number
SynCity: Using open data to create a synthetic city of hourly building energy estimates by integrating data-driven and physics-based methods	Energy consumption estimation	Prediction	Multi-source	Gradient boosting regression	[69]
The what, why, and how of changing cooling energy consumption in India's urban households	Energy consumption estimation	Factor analysis	Numerical	Statistical analysis	[126]
An explainable artificial intelligence approach to understanding drivers of economic energy consumption and sustainability	Energy consumption estimation	Factor analysis	Numerical	Deep neural network	[72]
Investigating the application of a transportation energy consumption prediction model for urban planning scenarios in machine learning and Shapley additive explanations method	Energy consumption estimation	Factor analysis	Numerical	Machine learning	[127]
Investigating application of a commercial and residential energy consumption prediction model for urban planning scenarios with machine learning and Shapley additive explanation methods	Energy consumption estimation	Factor analysis	Numerical	Machine learning	[20]
Fine-grained RNN with transfer learning for energy consumption estimation for EVs	Energy consumption estimation	Prediction	Numerical	Recurrent neural network, Transfer Learning	[75]
Analysis and forecast of China's energy consumption structure	Energy consumption estimation	Prediction	Numeric	Machine learning	[128]
Impact of urban expansion and in situ greenery on community-wide carbon emissions: Method development and insights from 11 US cities	Land use change and emission responses	Prediction	Image	Machine learning	[129]

Table A1. *Cont.*

Title	Topic	Goal	Data	Category	Source Ref. Number
A novel geospatial machine learning approach to quantify non-linear effects of land use/land cover change (LULCC) on carbon dynamics	Land use change and emission responses	Prediction	Image	Convolutionalneural networks	[34]
Multi-scenario land use/cover change and its impact on carbon storage based on the coupled GMOP-PLUS-InVEST model in the Hexi Corridor, China	Land use change and emission responses	Prediction	Image	Land use simulation	[130]
Spatial correlation evolution and prediction scenario of land use carbon emissions in the Yellow River Basin	Land use change and emission responses	Prediction	Multi-source	Land use simulation	[131]
Ecosystem carbon storage considering combined environmental and land use changes in the future and pathways to carbon neutrality in developed regions	Land use change and emission responses	Prediction	Multi-source	Artificial neural networks	[56]
Scenario simulation of land use change and carbon storage response in Henan Province, China: 1990–2050	Land use change and emission responses	Prediction	Multi-source	Land use simulation	[57]
A network-based framework for characterizing urban carbon metabolism associated with land use changes: A case of Beijing city, China	Land use change and emission, responses	Prediction	Multi-source	Land use simulation	[67]
Using explainable machine learning to understand how urban form shapes sustainable mobility	Land use change and emission responses	Factor analysis	Numerical	Gradient boosting decision trees	[33]
Built environment influences commute mode choice in a Global South megacity context: Insights from explainable machine learning approach	Land use change and emission responses	Factor analysis	Numerical	Machine learning	[132]

Table A1. *Cont.*

Title	Topic	Goal	Data	Category	Source Ref. Number
How changes in landscape patterns affect the carbon emission: a case study in the Chengdu-Chongqing Economic Circle, China	Land use change and emission responses	Prediction	Numerical	Statistical analysis	[133]
Unequal impacts of urban industrial land expansion on economic growth and carbon dioxide emissions	Land use change and emission responses	Factor analysis	Spatial	Machine learning	[134]
The nonlinear influence of land conveyance on urban carbon emissions: An interpretable ensemble learning-based approach	Land use change and emission responses	Factor analysis	Spatial	Gradient boosting decision trees	[66]
Spatial–temporal dynamics of land use carbon emissions and drivers in 20 urban agglomerations in China from 1990 to 2019	Land use change and emission responses	Factor analysis	Spatial	Geographically and temporally weighted regression, boosted regression trees	[135]
Implementing policies to mitigate urban heat islands: Analyzing urban development factors with an innovative machine learning approach	Land use change and emission responses	Factor analysis	Spatial	Decision trees, back-propagation neural network	[136]

References

1. Luqman, M.; Rayner, P.J.; Gurney, K.R. On the Impact of Urbanisation on CO_2 Emissions. *NPJ Urban Sustain.* **2023**, *3*, 6. [CrossRef]
2. Radford, A. Urban Design, Ethics and Responsive Cohesion. *Build. Res. Inf.* **2010**, *38*, 379–389. [CrossRef]
3. Ellis, C. Process and Principles in Urban Design. *J. Urban Des.* **2014**, *19*, 47–48. [CrossRef]
4. Stevens, N.J. Sociotechnical Urbanism: New Systems Ergonomics Perspectives on Land Use Planning and Urban Design. *Theor. Issues Ergon. Sci.* **2016**, *17*, 443–451. [CrossRef]
5. Son, T.H.; Weedon, Z.; Yigitcanlar, T.; Sanchez, T.; Corchado, J.M.; Mehmood, R. Algorithmic Urban Planning for Smart and Sustainable Development: Systematic Review of the Literature. *Sustain. Cities Soc.* **2023**, *94*, 104562. [CrossRef]
6. Song, C.; Deng, Z.; Zhao, W.; Yuan, Y.; Liu, M.; Xu, S.; Chen, Y. Developing Urban Building Energy Models for Shanghai City with Multi-Source Open Data. *Sustain. Cities Soc.* **2024**, *106*, 105425. [CrossRef]
7. Wu, J.; Li, C. Illustrating the Nonlinear Effects of Urban Form Factors on Transportation Carbon Emissions Based on Gradient Boosting Decision Trees. *Sci. Total Environ.* **2024**, *929*, 172547. [CrossRef]
8. Zhi, D.; Zhao, H.; Chen, Y.; Song, W.; Song, D.; Yang, Y. Quantifying the Heterogeneous Impacts of the Urban Built Environment on Traffic Carbon Emissions: New Insights from Machine Learning Techniques. *Urban Clim.* **2024**, *53*, 101765. [CrossRef]
9. Peng, Z.R.; Lu, K.F.; Liu, Y.; Zhai, W. The Pathway of Urban Planning AI: From Planning Support to Plan-Making. *J. Plan. Educ. Res.* **2023**. [CrossRef]
10. Chen, L.; Chen, Z.; Zhang, Y.; Liu, Y.; Osman, A.I.; Farghali, M.; Hua, J.; Al-Fatesh, A.; Ihara, I.; Rooney, D.W.; et al. Artificial Intelligence-Based Solutions for Climate Change: A Review. *Environ. Chem. Lett.* **2023**, *21*, 2525–2557. [CrossRef]
11. McDonald, J.; Li, B.; Frey, N.; Tiwari, D.; Gadepally, V.; Samsi, S. Great Power, Great Responsibility: Recommendations for Reducing Energy for Training Language Models. *arXiv* **2022**, arXiv:2205.09646.
12. Li, B.; Roy, R.; Wang, D.; Samsi, S.; Gadepally, V.; Tiwari, D. Toward Sustainable HPC: Carbon Footprint Estimation and Environmental Implications of HPC Systems. In *SC '23: Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*; Association for Computing Machinery: New York, NY, USA, 2023; pp. 1–15.
13. Filho, L.W.; Wall, T.; Rui Mucova, S.A.; Nagy, G.J.; Balogun, A.-L.; Luetz, J.M.; Ng, A.W.; Kovaleva, M.; Safiul Azam, F.M.; Alves, F.; et al. Deploying Artificial Intelligence for Climate Change Adaptation. *Technol. Forecast. Soc. Chang.* **2022**, *180*, 121662. [CrossRef]
14. Wang, J.; Biljecki, F. Unsupervised Machine Learning in Urban Studies: A Systematic Review of Applications. *Cities* **2022**, *129*, 103925. [CrossRef]
15. Tekouabou, K.S.C.; Diop, E.B.; Azmi, R.; Chenal, J. Artificial Intelligence Based Methods for Smart and Sustainable Urban Planning: A Systematic Survey. *Arch. Comput. Methods Eng.* **2023**, *30*, 1421–1438. [CrossRef]
16. Zappone, A.; Renzo, M.; Debbah, M. Wireless Networks Design in the Era of Deep Learning: Model-Based, AI-Based, or Both? *IEEE Trans. Commun.* **2019**, *67*, 7331–7376. [CrossRef]
17. Liu, Y.; Liu, X.; Gao, S.; Gong, L.; Kang, C.; Zhi, Y. Social Sensing: A New Approach to Understanding Our Socioeconomic Environments. *Ann. Assoc. Am. Geogr.* **2015**, *105*, 512–530. [CrossRef]
18. Schneider, A. Monitoring Land Cover Change in Urban and Peri-Urban Areas Using Dense Time Stacks of Landsat Satellite Data and a Data Mining Approach. *Remote Sens. Environ.* **2012**, *124*, 689–704. [CrossRef]
19. Arevalo-Ramirez, T.; Alfaro, A.; Figueroa, J.; Ponce-Donoso, M.; Saavedra, J.M.; Recabarren, M.; Delpiano, J. Challenges for Computer Vision as a Tool for Screening Urban Trees through Street-View Images. *Urban For. Urban Green.* **2024**, *95*, 128316. [CrossRef]
20. Amiri, S.; Mueller, M.; Hoque, S. Investigating the Application of a Commercial and Residential Energy Consumption Prediction Model for Urban Planning Scenarios with Machine Learning and Shapley Additive Explanation Methods. *Energy Build.* **2023**, *287*, 112965. [CrossRef]
21. Fang, Z.; Jin, Y.; Yang, T. Incorporating Planning Intelligence into Deep Learning: A Planning Support Tool for Street Network Design. *J. Urban Technol.* **2022**, *29*, 99–114. [CrossRef]
22. Alswedani, S.; Mehmood, R.; Katib, I. Sustainable Participatory Governance: Data-Driven Discovery of Parameters for Planning Online and in-Class Education in Saudi Arabia During COVID-19. *Front. Sustain. Cities* **2022**, *4*, 871171. [CrossRef]
23. Chen, M.; Xiao, H.; Zhao, H.; Liu, L. The Power of Attention: Government Climate-Risk Attention and Agricultural-Land Carbon Emissions. *Environ. Res.* **2024**, *251*, 118661. [CrossRef] [PubMed]
24. Nah, F.; Zheng, R.; Cai, J.; Siau, K.; Chen, L. Generative AI and ChatGPT: Applications, Challenges, and AI-Human Collaboration. *J. Inf. Technol. Case Appl. Res.* **2023**, *25*, 277–304.
25. Lee, D.B. Requiem for Large-Scale Models. *J. Am. Plan. Assoc.* **1973**, *39*, 163–178. [CrossRef]
26. Ritter, H.; Webber, M. Dilemmas in a General Theory of Planning. *Political Sci.* **1973**, *4*, 155–169.
27. Wang, F.; Harindintwali, J.D.; Yuan, Z.; Wang, M.; Wang, F.; Li, S.; Yin, Z.; Huang, L.; Fu, Y.; Li, L.; et al. Technologies and Perspectives for Achieving Carbon Neutrality. *Innovation* **2021**, *2*, 100180. [CrossRef] [PubMed]
28. Ravetza, J.; Neuvonenb, A.; Mäntysaloc, R. The New Normative: Synergistic Scenario Planning for Carbon-Neutral Cities and Regions. *Reg. Stud.* **2021**, *55*, 150–163. [CrossRef]
29. Keenan, T.F.; Williams, C.A. The Terrestrial Carbon Sink. *Annu. Rev. Environ. Resour.* **2018**, *43*, 219–243. [CrossRef]
30. Zhao, Q.; Jiang, M.; Zhao, Z.; Liu, F.; Zhou, L. The Impact of Green Innovation on Carbon Reduction Efficiency in China: Evidence from Machine Learning Validation. *Energy Econ.* **2024**, *133*, 107525. [CrossRef]

31. Buthelezi, M.; Lottering, R.; Peerbhay, K.; Mutanga, O. A Machine Learning Approach to Mapping Suitable Areas for Forest Vegetation in the EThekwini Municipality. *Remote Sens. Appl.* **2024**, *35*, 101208. [CrossRef]
32. Zhang, Y.; Teoh, B.; Wu, M.; Chen, J.; Zhang, L. Data-Driven Estimation of Building Energy and GHG Emissions Using Explainable Artificial Intelligence. *Energy* **2023**, *262*, 125468. [CrossRef]
33. Wagner, F.; Milojevic-Dupont, N.; Franken, L.; Zekar, A.; Thies, B.; Koch, N.; Creutzig, F. Using Explainable Machine Learning to Understand How Urban Form Shapes Sustainable Mobility. *Transp. Res. D Transp. Environ.* **2022**, *111*, 103442. [CrossRef]
34. Kang, J.; Zhang, B.; Dang, A. A Novel Geospatial Machine Learning Approach to Quantify Non-Linear Effects of Land Use/Land Cover Change (LULCC) on Carbon Dynamics. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *128*, 103712. [CrossRef]
35. Xu, Y.; Liu, Z.; Xue, W.; Yan, G.; Shi, X.; Zhao, D.; Zhang, Y.; Lei, Y.; Wang, J. Identification of On-Road Vehicle CO_2 Emission Pattern in China: A Study Based on a High-Resolution Emission Inventory. *Resour. Conserv. Recycl.* **2021**, *175*, 105891. [CrossRef]
36. Park, J.; Yang, B. GIS-Enabled Digital Twin System for Sustainable Evaluation of Carbon Emissions: A Case Study of Jeonju City, South Korea. *Sustainability* **2020**, *12*, 9186. [CrossRef]
37. Liang, X.; Li, X. Carbon Emission Causal Discovery and Multi-Step Forecasting for Global Cities. *Cities* **2024**, *148*, 104881. [CrossRef]
38. Bhatti, M.; Song, Z.; Bhatti, U.; Syam, M. AIoT-Driven Multi-Source Sensor Emission Monitoring and Forecasting Using Multi-Source Sensor Integration with Reduced Noise Series Decomposition. *J. Cloud Comput.* **2024**, *13*, 65. [CrossRef]
39. Shi, W.; Xiang, Y.; Ying, Y.; Jiao, Y.; Zhao, R.; Qiu, W. Predicting Neighborhood-Level Residential Carbon Emissions from Street View Images Using Computer Vision and Machine Learning. *Remote Sens.* **2024**, *16*, 1312. [CrossRef]
40. Javanmard, M.; Tang, Y.; Wang, Z.; Tontiwachwuthikul, P. Forecast Energy Demand, CO_2 Emissions and Energy Resource Impacts for the Transportation Sector. *Appl. Energy* **2023**, *338*, 120830. [CrossRef]
41. Cui, Q.; Zhang, S.; Huang, Y. Retail Commercial Space Clustering Based on Post-Carbon Era Context: A Case Study of Shanghai. In Proceedings of the 27th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), Sydney, Australia, 9–15 April 2022.
42. Zhang, X.; Sun, J.; Zhang, X.; Wang, F. Assessment and Regression of Carbon Emissions from the Building and Construction Sector in China: A Provincial Study Using Machine Learning. *J. Clean. Prod.* **2024**, *450*, 141903. [CrossRef]
43. Yang, K.; Zhou, P.; Wu, J.; Yao, Q.; Yang, Z.; Wang, X.; Wen, Y. Carbon Stock Inversion Study of a Carbon Peaking Pilot Urban Combining Machine Learning and Landsat Images. *Ecol. Indic.* **2024**, *159*, 111657. [CrossRef]
44. Tao, S.; Wu, X.; Fang, K.; Lin, D. Identifying Drivers of County-Level Industrial Carbon Intensity by a Generic Machine Learning Framework. *J. Clean. Prod.* **2024**, *454*, 142276. [CrossRef]
45. Lai, S.; Zhang, L.; Zeng, Y.; Deal, B. A Landscape Approach to Understanding Carbon Sequestration Assets at a State-Wide Scale for Sustainable Urban Planning. *Sustainability* **2024**, *16*, 3779. [CrossRef]
46. Myeong, S.; Nowak, D.; Duggin, M. A Temporal Analysis of Urban Forest Carbon Storage Using Remote Sensing. *Remote Sens. Environ.* **2006**, *101*, 277–282. [CrossRef]
47. Nowak, D.; Crane, D. Carbon Storage and Sequestration by Urban Trees in the USA. *Environ. Pollut.* **2002**, *116*, 381–389. [CrossRef] [PubMed]
48. Lu, Z.; Lin, F.; Ying, H. Design of Decision Tree via Kernelized Hierarchial Clustering for Multiclass Support Vector Machines. *Cybern. Syst.* **2007**, *38*, 187–202. [CrossRef]
49. Frey, U.; Klein, M.; Deissenroth, M. Modelling Complex Investment Decisions in Germany for Renewables with Different Machine Learning Algorithms. *Environ. Model. Softw.* **2019**, *118*, 61–75. [CrossRef]
50. Gleason, C.; Im, J. Forest Biomass Estimation from Airborne LiDAR Data Using Machine Learning Approaches. *Remote Sens. Environ.* **2012**, *125*, 80–91. [CrossRef]
51. Wu, X.; Shen, J.; Wang, M.; Lee, K.Y. Intelligent Predictive Control of Large-Scale Solvent-Based CO_2 Capture Plant Using Artificial Neural Network and Particle Swarm Optimization. *Energy* **2020**, *196*, 117070. [CrossRef]
52. Li, F.; Zhang, J.; Shang, C.; Huang, D.; Oko, E.; Wang, M. Modelling of a Post-Combustion CO_2 Capture Process Using Deep Belief Network. *Appl. Therm. Eng.* **2018**, *130*, 997–1003. [CrossRef]
53. Zhang, C.; Song, T.; Shi, R.; Hou, Z.; Wu, N.; Zhang, H.; Zhuo, W. Estimating the Forest Carbon Storage of Chongming Eco-Island, China, Using Multisource Remotely Sensed Data. *Remote Sens.* **2023**, *15*, 1575. [CrossRef]
54. Zhang, Z.; Jiang, W.; Peng, K.; Wu, Z.; Ling, Z.; Li, Z. Assessment of the Impact of Wetland Changes on Carbon Storage in Coastal Urban Agglomerations from 1990 to 2035 in Support of SDG15.1. *Sci. Total Environ.* **2023**, *877*, 162824. [CrossRef]
55. Chao, M.; Maimai, W.; Hanzhang, L.; Zhibo, C.; Xiaohui, C. A Spatio-Temporal Neural Network Learning System for City-Scale Carbon Storage Capacity Estimating. *IEEE Access* **2023**, *11*, 31304–31322. [CrossRef]
56. Liu, J.; Yan, Q.; Zhang, M. Ecosystem Carbon Storage Considering Combined Environmental and Land-Use Changes in the Future and Pathways to Carbon Neutrality in Developed Regions. *Sci. Total Environ.* **2023**, *903*, 166204. [CrossRef]
57. Fan, L.; Cai, T.; Wen, Q.; Han, J.; Wang, S.; Wang, J.; Yin, C. Scenario Simulation of Land Use Change and Carbon Storage Response in Henan Province, China: 1990–2050. *Ecol. Indic.* **2023**, *154*, 110660. [CrossRef]
58. Jiang, H.; Guo, H.; Sun, Z.; Yan, X.; Zha, J.; Zhang, H.; Li, S. Urban-Rural Disparities of Carbon Storage Dynamics in China's Human Settlements Driven by Population and Economic Growth. *Sci. Total Environ.* **2023**, *871*, 162092. [CrossRef] [PubMed]
59. Han, J.; Meng, X.; Zhou, X.; Yi, B.; Liu, M.; Xiang, W.-N. A Long-Term Analysis of Urbanization Process, Landscape Change, and Carbon Sources and Sinks: A Case Study in China's Yangtze River Delta Region. *J. Clean. Prod.* **2017**, *141*, 1040–1050. [CrossRef]

60. Larsen, H.N.; Hertwich, E.G. Implementing Carbon-Footprint-Based Calculation Tools in Municipal Greenhouse Gas Inventories: The Case of Norway. *J. Ind. Ecol.* **2010**, *14*, 965–977. [CrossRef]
61. Hobbs, T.J.; Neumann, C.R.; Meyer, W.S.; Moon, T.; Bryan, B.A. Models of Reforestation Productivity and Carbon Sequestration for Land Use and Climate Change Adaptation Planning in South Australia. *J. Environ. Manag.* **2016**, *181*, 279–288. [CrossRef]
62. Pan, H.; Zhang, L.; Cong, C.; Deal, B.; Wang, Y. A Dynamic and Spatially Explicit Modeling Approach to Identify the Ecosystem Service Implications of Complex Urban Systems Interactions. *Ecol. Indic.* **2019**, *102*, 426–436. [CrossRef]
63. Kwak, Y.; Deal, B. Multi-Scaled Green Infrastructure Optimization: Spatial Projections and Assessment for Dynamic Planning and Design. *Landsc. Urban Plan.* **2024**, *249*, 105128. [CrossRef]
64. Liang, X.; Guan, Q.; Clarke, K.; Liu, S.; Wang, B.; Yao, Y. Understanding the Drivers of Sustainable Land Expansion Using a Patch-Generating Land Use Simulation (PLUS) Model: A Case Study in Wuhan, China. *Comput. Environ. Urban Syst.* **2021**, *85*, 101569. [CrossRef]
65. Pielke, R.A.; Marland, G.; Betts, R.A.; Chase, T.N.; Eastman, J.L.; Niles, J.O.; Niyogi, D.D.S.; Running, S.W. The Influence of Land-Use Change and Landscape Dynamics on the Climate System: Relevance to Climate-Change Policy beyond the Radiative Effect of Greenhouse Gases. *Philos. Trans. R. Soc. Lond. A Math. Phys. Eng. Sci.* **2002**, *360*, 1705–1719. [CrossRef] [PubMed]
66. Qiao, R.; Wu, Z.; Jiang, Q.; Liu, X.; Gao, S.; Xia, L.; Yang, T. The Nonlinear Influence of Land Conveyance on Urban Carbon Emissions: An Interpretable Ensemble Learning-Based Approach. *Land Use Policy* **2024**, *140*, 107117. [CrossRef]
67. Wei, J.; Xia, L.; Chen, L.; Zhang, Y.; Yang, Z. A Network-Based Framework for Characterizing Urban Carbon Metabolism Associated with Land Use Changes: A Case of Beijing City, China. *J. Clean. Prod.* **2022**, *371*, 133695. [CrossRef]
68. Liu, J.; Pei, X.; Zhu, W.; Jiao, J. Multi-Scenario Simulation of Carbon Budget Balance in Arid and Semi-Arid Regions. *J. Environ. Manag.* **2023**, *346*, 119016. [CrossRef] [PubMed]
69. Roth, J.; Martin, A.; Miller, C.; Jain, R. SynCity: Using Open Data to Create a Synthetic City of Hourly Building Energy Estimates by Integrating Data-Driven and Physics-Based Methods. *Appl. Energy* **2010**, *280*, 115981. [CrossRef]
70. Howard, B.; Parshall, L.; Thompson, J.; Hammer, S.; Dickinson, J.; Modi, V. Spatial Distribution of Urban Building Energy Consumption by End Use. *Energy Build.* **2012**, *45*, 141–151. [CrossRef]
71. Robinson, C.; Dilkina, B.; Hubbs, J.; Zhang, W.; Guhathakurta, S.; Brown, M.A.; Pendyala, R.M. Machine Learning Approaches for Estimating Commercial Building Energy Consumption. *Appl. Energy* **2017**, *208*, 889–904. [CrossRef]
72. Srivastava, P.; Mangla, S.; Eachempati, P.; Tiwari, A. An Explainable Artificial Intelligence Approach to Understanding Drivers of Economic Energy Consumption and Sustainability. *Energy Econ.* **2023**, *125*, 106868. [CrossRef]
73. Kavgic, M.; Mavrogianni, A.; Mumovic, D.; Summerfield, A.; Stevanovic, Z.; Djurovic-Petrovic, M. A Review of Bottom-up Building Stock Models for Energy Consumption in the Residential Sector. *Build. Environ.* **2010**, *45*, 1683–1697. [CrossRef]
74. Kristensen, M.; Hedegaard, R.; Petersen, S. Long-Term Forecasting of Hourly District Heating Loads in Urban Areas Using Hierarchical Archetype Modeling. *Energy* **2020**, *201*, 117687. [CrossRef]
75. Hua, Y.; Sevegnani, M.; Yi, D.; Birnie, A.; McAslan, S. Fine-Grained RNN With Transfer Learning for Energy Consumption Estimation on EVs. *IEEE Trans. Industr. Inform.* **2022**, *18*, 8182–8190. [CrossRef]
76. Jiang, H.; Yin, J.; Wei, D.; Luo, X.; Ding, Y.; Xia, R. Industrial Carbon Emission Efficiency Prediction and Carbon Emission Reduction Strategies Based on Multi-Objective Particle Swarm Optimization-Backpropagation: A Perspective from Regional Clustering. *Sci. Total Environ.* **2024**, *906*, 167692. [CrossRef]
77. Klosterman, R.E. Planning Support Systems: A New Perspective on Computer-Aided Planning. *J. Plan. Educ. Res.* **1997**, *17*, 45–54. [CrossRef]
78. Li, P.; Xu, T.; Wei, S.; Wang, Z.-H. Multi-Objective Optimization of Urban Environmental System Design Using Machine Learning. *Comput. Environ. Urban Syst.* **2022**, *94*, 101796. [CrossRef]
79. Aghajan-Eshkevari, S.; Ameli, M.; Azad, S. Optimal Routing and Power Management of Electric Vehicles in Coupled Power Distribution and Transportation Systems. *Appl. Energy* **2023**, *341*, 121126. [CrossRef]
80. Guan, L. Reaching Carbon Neutrality Requires Energy-Efficient Training of AI. *Nature* **2024**, *626*, 33. [CrossRef]
81. Lin, J.; Lu, S.; He, X.; Wang, F. Analyzing the Impact of Three-Dimensional Building Structure on CO_2 Emissions Based on Random Forest Regression. *Energy* **2021**, *236*, 121502. [CrossRef]
82. Subramaniam, N.; Yusof, N. Modelling of CO_2 Emission Prediction for Dynamic Vehicle Travel Behavior Using Ensemble Machine Learning Technique. In Proceedings of the IEEE 19th Student Conference on Research and Development (SCOReD), Kota Kinabalu, Malaysia, 23–25 November 2021; pp. 383–387.
83. Ludwig, J.; Kling, J.; Mullainathan, S. Mechanism Experiments and Policy Evaluations. *J. Econ. Perspect.* **2011**, *25*, 17–38. [CrossRef]
84. Hahn, R.; Metcalfe, R. The Impact of Behavioral Science Experiments on Energy Policy. *Econ. Energy Environ. Policy* **2016**, *5*, 27–44. [CrossRef]
85. Urban, A.; Hick, D.; Noennig, J.; Kammer, D. With a Little Help from AI: Pros and Cons of AI in Urban Planning and Participation. *Int. J. Urban Plan. Smart Cities* **2021**, *2*, 19–33. [CrossRef]
86. Deshpande, A.; Sharp, H. Responsible AI Systems: Who Are the Stakeholders? In *AIES '22: Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*; Association for Computing Machinery: New York, NY, USA, 2022.
87. Rajkomar, A.; Hardt, M.; Howell, M.D.; Corrado, G.; Chin, M.H. Ensuring Fairness in Machine Learning to Advance Health Equity. *Ann. Intern. Med.* **2018**, *169*, 866–872. [CrossRef]

88. Mihunov, V.; Wang, K.; Wang, Z.; Lam, N.; Sun, M. Social Media and Volunteer Rescue Requests Prediction with Random Forest and Algorithm Bias Detection: A Case of Hurricane Harvey. *Environ. Res. Commun.* **2023**, *5*, 065013. [CrossRef]
89. Siau, K.; Wang, W. Artificial Intelligence (AI) Ethics: Ethics of AI and Ethical AI. *J. Database Manag.* **2020**, *31*, 74–87. [CrossRef]
90. Page, J.; Mörtberg, U.; Destouni, G.; Ferreira, C.; Näsström, H.; Kalantari, Z. Open-Source Planning Support System for Sustainable Regional Planning: A Case Study of Stockholm County, Sweden. *Environ. Plan. B Urban Anal. City Sci.* **2020**, *47*, 1508–1523. [CrossRef]
91. Zhong, J.; Zhong, Y.; Han, M.; Yang, T.; Zhang, Q. The Impact of AI on Carbon Emissions: Evidence from 66 Countries. *Appl. Econ.* **2024**, *56*, 2975–2989. [CrossRef]
92. Lacoste, A.; Luccioni, A.S.; Schmidt, V.; Dandres, T. Quantifying the Carbon Emissions of Machine Learning. *arXiv* **2019**, arXiv:1910.09700.
93. Karvonen, A.; Cook, M.; Haarstad, H. Urban Planning and the Smart City: Projects, Practices and Politics. *Urban Plan.* **2020**, *5*, 65–68. [CrossRef]
94. Cong, C.; Pan, H.; Page, J.; Barthel, S.; Kalantari, Z. Modeling Place-Based Nature-Based Solutions to Promote Urban Carbon Neutrality. *Ambio* **2023**, *52*, 1297–1313. [CrossRef]
95. Pan, H.; Page, J.; Shi, R.; Cong, C.; Cai, Z.; Barthel, S.; Thollander, P.; Colding, J.; Kalantari, Z. Contribution of Prioritized Urban Nature-Based Solutions Allocation to Carbon Neutrality. *Nat. Clim. Chang.* **2023**, *13*, 862–870. [CrossRef]
96. Ye, X.; Du, J.; Ye, Y. MasterplanGAN: Facilitating the Smart Rendering of Urban Master Plans via Generative Adversarial Networks. *Environ. Plan. B* **2022**, *49*, 794–814. [CrossRef]
97. Calixto, V.; Canuto, R.; Noronha, M.; Afrooz, A.; Gu, N.; Celani, G. A Layered Approach for the Data-Driven Design of Smart Cities. In Proceedings of the 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), Hongkong, China, 29 March–1 April 2021; pp. 739–748.
98. Dawes, S.S.; Vidiasova, L.; Parkhimovich, O. Planning and Designing Open Government Data Programs: An Ecosystem Approach. *Gov. Inf. Q.* **2016**, *33*, 15–27. [CrossRef]
99. Royo, S.; Yetano, A. "Crowdsourcing" as a Tool for e-Participation: Two Experiences Regarding CO_2 Emissions at Municipal Level. *Electron. Commer. Res.* **2015**, *15*, 323–348. [CrossRef]
100. Goodspeed, R. Digital Knowledge Technologies in Planning Practice: From Black Boxes to Media for Collaborative Inquiry. *Plan. Theory Pract.* **2016**, *17*, 577–600. [CrossRef]
101. te Brömmelstroet, M. Towards a Pragmatic Research Agenda for the PSS Domain. *Transp. Res. Part. A Policy Pract.* **2017**, *104*, 77–83. [CrossRef]
102. Lybeck, R. Mobile Participation in Urban Planning: Exploring a Typology of Engagement. *Plan. Pract. Res.* **2018**, *33*, 523–539. [CrossRef]
103. Kurniawan, M.; de Vries, W. The Contradictory Effects in Efficiency and Citizens' Participation When Employing Geo-ICT Apps within Local Government. *Local Gov. Stud.* **2015**, *41*, 119–136. [CrossRef]
104. Mergel, I. Distributed Democracy: SeeClickFix.Com for Crowdsourced Issue Reporting. 2012. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1992968 (accessed on 2 April 2024).
105. Desouza, K.C.; Bhagwatwar, A. Technology-Enabled Participatory Platforms for Civic Engagement: The Case of U.S. Cities. *J. Urban Technol.* **2014**, *21*, 25–50. [CrossRef]
106. Hollands, R. Will the Real Smart City Please Stand Up? *City* **2008**, *12*, 303–320. [CrossRef]
107. Mundaca, L.; Zhu, X.; Hackenfort, M. Behavioural Insights for Sustainable Energy Use. *Energy Policy* **2022**, *171*, 113292. [CrossRef]
108. Russo, P.; Lanzilotti, R.; Costabile, M.F.; Pettit, C.J. Adoption and Use of Software in Land Use Planning Practice: A Multiple-Country Study. *Int. J. Hum. Comput. Interact.* **2018**, *34*, 57–72. [CrossRef]
109. Yigitcanlar, T.; Mehmood, R.; Corchado, J.M. Green Artificial Intelligence: Towards an Efficient, Sustainable and Equitable Technology for Smart Cities and Futures. *Sustainability* **2021**, *13*, 8996. [CrossRef]
110. Uniyal, S.; Purohit, S.; Chaurasia, K.; Rao, S.; Amminedu, E. Quantification of Carbon Sequestration by Urban Forest Using Landsat 8 OLI and Machine Learning Algorithms in Jodhpur, India. *Urban For. Urban Green.* **2022**, *67*, 127445. [CrossRef]
111. Lee, Y.; Son, B.; Im, J.; Zhen, Z.; Quackenbush, L. Two-Step Carbon Storage Estimation in Urban Human Settlements Using Airborne LiDAR and Sentinel-2 Data Based on Machine Learning. *Urban For. Urban Green.* **2024**, *94*, 128239. [CrossRef]
112. Zhang, F.; Tian, X.; Zhang, H.; Jiang, M. Estimation of Aboveground Carbon Density of Forests Using Deep Learning and Multisource Remote. *Remote Sens.* **2022**, *14*, 3022. [CrossRef]
113. Huang, C.; Zhang, G.; Yin, M.; Yao, J. Energy-Driven Intelligent Generative Urban Design, Based on Deep Reinforcement Learning Method with a Nested Deep Q-R Network. In Proceedings of the 27th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), Sydney, Australia, 9–15 April 2022; pp. 233–242.
114. Zhang, X.; Yan, F.; Liu, H.; Qiao, Z. Towards Low-Carbon Cities: A Machine Learning Method for Predicting Urban Blocks Carbon Emissions Based on Built Environment Factors in Changxing City, China. *Sustain. Cities Soc.* **2021**, *69*, 102875. [CrossRef]
115. Kaiser, B.C.S.; Santos, R.S.; Caiado, R.G.G.; Scavarda, L.F.; Netto, P.I. Efficiency Assessment of Public Transport Vehicles Using Machine Learning and Non-Parametric Models. In Proceedings of the International Joint Conference on Industrial Engineering and Operations Management, Lisbon, Portugal, 28–30 June 2023.
116. Amiri, S.; Mottahedi, S.; Lee, E.R.; Hoque, S. Peeking inside the Black-Box: Explainable Machine Learning Applied to Household Transportation Energy Consumption. *Comput. Environ. Urban Syst.* **2021**, *88*, 101647. [CrossRef]

117. Tanteliniaina, M.; Andrianarimanana, M. Generic Above-Ground Biomass Estimator for Urban Forests Using Machine Learning. *Arboric. J.* **2022**, *45*, 334–350. [CrossRef]
118. Almubaidin, M.A.; Ismail, N.S.; Latif, S.D.; Ahmed, A.N.; Dullah, H.; El-Shafie, A.; Sonne, C. Machine Learning Predictions for Carbon Monoxide Levels in Urban Environments. *Results Eng.* **2024**, *22*, 102114. [CrossRef]
119. Sokama-Neuyam, Y.A.; Amezah, S.M.; Adjei, S.; Adenutsi, C.D.; Erzuah, S.; Quaye, J.A.; Ampomah, W.; Sarkodie, K. Predictive Modeling of Energy-Related Greenhouse Gas Emissions in Ghana towards a Net-Zero Future. *Greenh. Gases Sci. Technol.* **2024**, *14*, 42–61. [CrossRef]
120. Niu, D.; Wang, K.; Wu, J.; Sun, L.; Liang, Y.; Xu, X.; Yang, X. Can China Achieve Its 2030 Carbon Emissions Commitment? Scenario Analysis Based on an Improved General Regression Neural Network. *J. Clean Prod.* **2020**, *243*, 118558. [CrossRef]
121. Anthony, L.; Kanding, B.; Selvan, R. Carbontracker: Tracking and Predicting the Carbon Footprint of Training Deep Learning Models. *arXiv* **2020**, arXiv:2007.03051.
122. Javanmard, M.; Tang, Y.; Martínez-Hernández, J. Forecasting Air Transportation Demand and Its Impacts on Energy and Emission. *Appl. Energy* **2024**, *364*, 123031. [CrossRef]
123. Park, C.; Jeong, S.; Kim, C.; Shin, J.; Joo, J. Machine Learning Based Estimation of Urban On-Road CO_2 Concentration in Seoul. *Environ. Res.* **2023**, *231*, 116256. [CrossRef] [PubMed]
124. Aras, S.; Van, M. An Interpretable Forecasting Framework for Energy and CO_2 Emissions. *Appl. Energy* **2022**, *328*, 120163. [CrossRef]
125. Ji, Z.; Song, H.; Lei, L.; Sheng, M.; Guo, K.; Zhang, S. A Novel Approach for Predicting Anthropogenic CO_2 Emissions Using Machine Learning Based on Clustering of the CO_2 Concentration. *Atmosphere* **2024**, *15*, 323. [CrossRef]
126. Khosla, R.; Agarwal, A.; Sircar, N.; Chatterjee, D. The What, Why, and How of Changing Cooling Energy Consumption in India's Urban Households. *Environ. Res. Lett.* **2021**, *16*, 044035. [CrossRef]
127. Amiri, S.; Mueller, M.; Hoque, S. Investigating the Application of a Transportation Energy Consumption Prediction Model for Urban Planning Scenarios in Machine Learning and Shapley Additive Explanations Method. *J. Sustain. Res.* **2022**, *4*, e220001.
128. Zeng, S.; Su, B.; Zhang, M.; Gao, Y.; Liu, J.; Luo, S.; Tao, Q. Analysis and Forecast of China's Energy Consumption Structure. *Energy Policy* **2021**, *159*, 112630. [CrossRef]
129. Milnar, M.; Ramaswami, A. Impact of Urban Expansion and In Situ Greenery on Community-Wide Carbon Emissions: Method Development and Insights from 11 US Cities. *Environ. Sci. Technol.* **2020**, *54*, 16086–16096. [CrossRef]
130. Zhang, Y.; Naerkezi, N.; Zhang, Y.; Wang, B. Multi-Scenario Land Use/Cover Change and Its Impact on Carbon Storage Based on the Coupled GMOP-PLUS-InVEST Model in the Hexi Corridor, China. *Sustainability* **2024**, *16*, 1402. [CrossRef]
131. Rong, T.; Zhang, P.; Li, G.; Wang, Q.; Zheng, H.; Chang, Y.; Zhang, Y. Spatial Correlation Evolution and Prediction Scenario of Land Use Carbon Emissions in the Yellow River Basin. *Ecol. Indic.* **2023**, *154*, 110701. [CrossRef]
132. Ashik, F.R.; Sreezon, A.I.Z.; Rahman, M.H.; Zafri, N.M.; Labib, S.M. Built Environment Influences Commute Mode Choice in a Global South Megacity Context: Insights from Explainable Machine Learning Approach. *J. Transp. Geogr.* **2024**, *116*, 103828. [CrossRef]
133. Tang, Z.; Xiao, Y.; Wang, Y. How Changes in Landscape Patterns Affect the Carbon Emission: A Case Study in the Chengdu-Chongqing Economic Circle, China. *Environ. Monit. Assess.* **2024**, *196*, 158. [CrossRef]
134. Yoo, C.; Xiao, H.; Zhong, Q.; Weng, Q. Unequal Impacts of Urban Industrial Land Expansion on Economic Growth and Carbon Dioxide Emissions. *Commun. Earth Environ.* **2024**, *5*, 1375. [CrossRef]
135. Pu, X.; Cheng, Q.; Chen, H. Spatial–Temporal Dynamics of Land Use Carbon Emissions and Drivers in 20 Urban Agglomerations in China from 1990 to 2019. *Environ. Sci. Pollut. Res.* **2023**, *30*, 107854–107877. [CrossRef]
136. Wang, S.; Ou, H.; Chen, P.; Lin, T. Implementing Policies to Mitigate Urban Heat Islands: Analyzing Urban Development Factors with an Innovative Machine Learning Approach. *Urban Clim.* **2024**, *55*, 101868. [CrossRef]