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Initial Systems-Level Assessment of a Distributed Direct Air Capture System Concept at the Urban-scale (UrbanDAC)

Thomaz Kobayashi-Carvalhaes, Ph.D.
Nasir Ahmad, Ph.D.

August 2023

OAK RIDGE National Laboratory

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Geospatial Science & Human Security Division

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OAK RIDGE NATIONAL LABORATORY
Oak Ridge, TN 37831
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ABSTRACT

Direct Air Capture (DAC) systems offer a promising solution for mitigating global carbon emissions by directly removing ambient carbon dioxide (CO2) from the atmosphere. While future DAC facilities are typically envisioned as being large and centralized, small-scale systems present an alternative approach with advantages such as adaptability and lower uptake costs. By harnessing waste heat from the built environment, such small-scale systems become distributed DAC at the urban scale (UrbanDAC) that benefit from existing urban infrastructure, while presenting challenges such as identifying eligible buildings and sustainable transportation and storage of captured CO2. Collaborating with engineering experts and developers of a DAC unit that can be co-located with cooling towers of existing commercial buildings, this study explores the systems-level implications of UrbanDAC using a geographically explicit multi-decision criteria analysis (MCDA) framework. By considering various infrastructure and environmental factors, network analysis and geospatial techniques are applied to identify optimal building candidates for distributed DAC units within Knoxville, Tennessee, USA, as a representative mid-size city. The selected outputs of the MCDA are used to explore a scenario that assumes a CO2 collection and transport route for 20 high-ranking candidate buildings; total carbon emissions, EV energy consumption, and net carbon dioxide removal (CDR) are then calculated. Results suggest that the spatial variation of optimal candidates between thriving commercial areas is an important planning consideration. Examining the feasibility of UrbanDAC at an urban planning level provides valuable insights into the barriers and enabling conditions for CDR in cities, where the vast majority of CO2 emissions are produced, and supports decision-making processes for the implementation of decarbonization initiatives. Through this initial assessment, this research acts as a pilot study for an emerging technology that highlights the importance of distributed DAC technologies in addressing climate change and emphasizes the need for further research and exploration in this domain.

1. INTRODUCTION

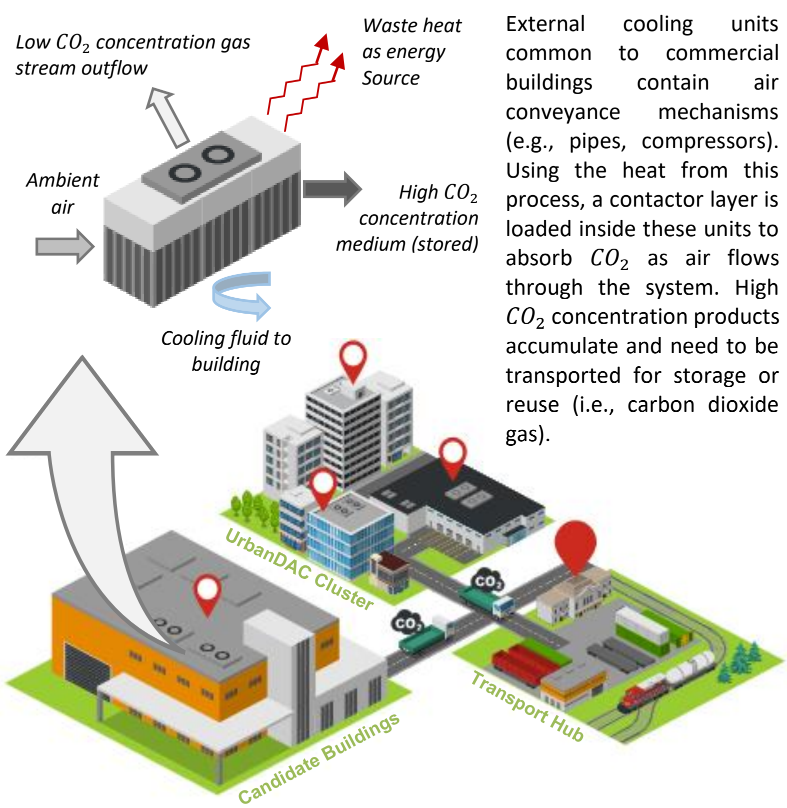
1.1 BACKGROUND & MOTIVATION

Driven mainly by escalating carbon dioxide (CO_2) emissions, climate change necessitates urgent actions to mitigate the oncoming impacts to communities and economies such as those driven by increased extreme weather, excessive heat, and drought [1], [2]. While efforts to reduce emissions at their source are crucial, additional approaches like carbon dioxide removal (CDR) are gaining prominence. Among these approaches, Direct Air Capture (DAC) systems directly extract CO_2 from ambient air, irrespective of emission sources, thereby aiding in climate change mitigation efforts [3]–[5]. The current paradigm for DAC technology predominantly focuses on large-scale centralized facilities with heating and air conveyance to capture carbon that is either stored indefinitely (e.g., subterranean pumping) or repurposed by the manufacturing industry [3] [6]. Therefore, DAC implementation faces challenges such as high energy requirements, cost-effectiveness, and the development of sustainable and scalable deployment strategies, which necessitate further research and technological advancements [7], [8].

New technologies are emerging at the cutting edge of DAC that offer a viable alternative to large facilities by harnessing small-scale systems that adapt to existing structures in commercial buildings [9]–[11]. In this report, we focus on one patent-pending example that capitalizes on waste heat produced by external cooling towers already present throughout the building stock of urban areas [12]. These systems offer the potential to achieve CDR at a local level while efficiently utilizing existing resources, resulting in energy, material, and cost savings. The integration of DAC systems with commercial building infrastructure transforms these structures into carbon capture nodes distributed within the urban fabric. We term this a form of distributed direct air capture at the urban scale, or 'UrbanDAC'. See Box 1 for a brief explanation of the UrbanDAC concept and use-case technology. This decentralized approach not only provides flexibility and adaptability but also reduces the need for significant energy consumption and siting barriers associated with large-scale DAC facilities.

With advantages such as modularity, lower energy demands, and cost-effectiveness, this distributed approach offers a unique opportunity for cities to tailor plans for DAC system deployment to achieve net-zero and GHG reduction goals [13]–[16]. However, to ensure the success of UrbanDAC, important factors must be considered, such as identification and optimal selection of eligible buildings, resilience to service disruptions due to natural disasters and other

Box 1. Co-locating small-scale DAC units with existing cooling systems in the building stock.



External cooling units common to commercial buildings contain air conveyance mechanisms (e.g., pipes, compressors). Using the heat from this process, a contactor layer is loaded inside these units to absorb CO_2 as air flows through the system. High CO_2 concentration products accumulate and need to be transported for storage or reuse (i.e., carbon dioxide gas).

risks, and overall sustainability at the systems-level. Moreover, it is necessary to consider interconnectivity, since the implementation of UrbanDAC is feasible due to the inherent capabilities of urban systems (the collective systems, organizations, and physical infrastructure that manage the energy and material flows within an urban area), as exemplified by the transportation-dependent network of waste treatment facilities, landfills, and numerous refuse-generating buildings throughout a city in the case of waste removal systems. Therefore, strategies and assessments are necessary to identify eligible buildings and select optimal candidates for UrbanDAC such that service disruption and energy consumption associated with continuous CO_2 transport and storage are minimized.

1.2 OBJECTIVES

This assessment aimed to explore one of the potential ways UrbanDAC technologies can evolve as interconnected and interdependent infrastructure systems, and to produce coarse quantifications of distance and energy-based metrics to serve toward comparative analyses against traditional, centralized DAC scenarios. To support decision making, a sustainability assessment was developed that includes mapping relevant factors in urban areas for identifying candidate buildings, selecting the most suitable for UrbanDAC implementation, determining optimal CO_2 transport routes based on optimal spatial distribution of UrbanDAC, and estimating potential distance and energy-related metrics for selected urban scenarios (i.e., site selection and routing results). Specifically, this study was bounded by the following primary and sub-objectives:

i. Maximize CDR at the system-level by optimizing UrbanDAC distribution and network structure for minimal service disruption and maximum efficiency.

    a. Identify city-scale spatial constraints for UrbanDAC performance.

    b. Optimize candidate buildings based on characteristics of the integrated infrastructure network and natural-built environment characteristics.

ii. Pilot an integrated assessment strategy for exploring the implications of UrbanDAC siting, systems-level design, and implementation.

The proposed approach leverages a systems perspective (i.e., cities as complex systems) and an actionable unit of analysis (i.e., the city as an administrative unit) for decision-making and implementation by framing DAC as a networked part of a broader urban system. While it is possible to generate aggregate outcomes from deterministic metrics based on the performance of a single engineered unit (e.g., scaling the CO_2 capture rate of a DAC unit at average performance), this does not account for energy demands and possible emissions through the respective carbon lifecycle (i.e., net CDR), nor the DAC-relevant natural and built environment dynamics that change from place to place across urban spaces (i.e., spatially dependent factors and outcomes). Toward a decision-making framework that includes urban-scale pathways and systems-level implications, this study considered environmental, infrastructural, and network-oriented factors in a multi-method multi-criteria decision analysis framework. This offers a critical starting point for UrbanDAC research throughout the community.

1.3 PROPOSED FRAMEWORK FOR URBANDAC R&D

To properly assess the potential impact of distributed DAC as a mitigation strategy, it is crucial to consider the multi-dimensional urban dynamics and infrastructure that affect net CDR performance for UrbanDAC at the systems-level. In this study, these considerations included the eligibility of existing buildings (i.e., structures with cooling towers), possible storage hubs, place-based siting criteria (e.g., proximity to other candidates, humidity), infrastructure network criteria (e.g., traffic, road centrality), and risk-based considerations (e.g., flooding-induced road impairments, traffic delays, and rerouting). By considering both the suitability of candidate buildings for DAC deployment and the efficiency and resilience of the network connecting these units, the location and performance of UrbanDAC systems could be optimized. Therefore, a two-part data-driven framework composed of geospatial and network analyses was proposed.

The geospatial analysis aimed to identify and rank optimal locations for DAC systems in an urban environment using publicly available data, such as building characteristics, flood risk, and zoning regulations, and integrated these spatial attributes to generate suitability maps highlighting areas with high potential for effective UrbanDAC deployment. The network analysis focuses on UrbanDAC as an infrastructure system with units interconnected by roads that transport captured carbon to key hubs. Like the suitability analysis, weights were assigned to network links (i.e., roads as graph edges) signifying vulnerabilities (e.g., flood risk) and friction (e.g., inefficiencies like traffic) to assess the efficiency and likelihood of disruption among candidate buildings. Some buildings can be located within advantageous points in the network that are highly accessible with many alternative routes that can be taken to an endpoint in the case of a disruption [17]. In this way, resilience was linked to sustainability, where disruptions cause unequally distributed delays, costs, and impacts to CO_2 capture rates and cumulative CDR [18].

Publicly available geographic information, such as GIS data (e.g., shapefile, geodatabase) or datasets that can be georeferenced (i.e., via attributes such as addresses, zipcodes), enables the simultaneous evaluation of the multiple criteria for suitability and network analysis through spatial relationships between datasets. Therefore, the two-part methodology (i.e., suitability and network analyses) was framed within a multi-criteria decision analysis (MCDA) framework. MCDA is useful for exploratory assessments because it enables choosing multiple alternative sets of criteria and weights in a scenario-based fashion oriented to specific goals (e.g., maximizing total annual carbon capture) - a necessary exercise for complex, multi-dimensional, and uncertain problem domains such as sustainable development of novel technologies where authoritative considerations are not yet established [19].

The geospatial MCDA framework was applied to Knoxville, TN, to demonstrate applicability to mid-size US city. Knoxville has a diverse urban landscape that has experienced steady population growth and the evolving demands associated with a growing cityscape, and thus, serves as an ideal testbed for evaluating the effectiveness and feasibility of distributed DAC systems in an urban context. The selection of Knoxville was also driven by the availability of relevant geospatial data and infrastructure information. In addition to assuming implementation in a mid-size US city, for the final urban scenario (see 2.6 and 3.3), we also assume immediate deployment using traditional transporter vehicles with compression ignition engines (i.e., gasoline or diesel) that collect CO_2 from UrbanDAC buildings and imply carbon emissions, as well as a brief scenario assuming EV transporter vehicles. This case study enables valuable insights into the challenges, opportunities, and implications of implementing DAC technologies in a real-world urban environment, contributing to the knowledge, and understanding of sustainable urban development and carbon dioxide mitigation strategies.

2. METHODOLOGY

2.1 OVERVIEW

Figure 1 summarizes the methodology consisting of identifying commercial buildings (see 2.2) and a two-part combination of suitability and network analyses enabled by Multi-Criteria Decision Analysis (MCDA) and geospatial data (see 2.3). The suitability analysis followed a geospatial approach to develop a series of composite indices using a layered reclassification method (see 2.4). The network analysis approach focused on ensuring the resilience of the UrbanDAC system as an integral part of the urban system by measuring how accessible a node (e.g., building) is through multiple alternate routes from key locations (e.g., carbon hubs, storage; see 2.5). The two approaches were then integrated where the candidate buildings' location and the edge weights as 'friction' are used to rank the candidates such that a building with a higher ranking is accessible through more routes with minimum friction.

Using the results, scenarios were selected to illustrate a bundle of decision considerations in choosing an optimal UrbanDAC distribution, where risks at each location and risks on the road network that connects those locations are minimized. The scenarios were based on a subset of top candidates selected for the generation of an optimized route for the pick-up and transport of CO_2 captured at the buildings (see 2.5.2). The generated route was then used for rudimentary calculations of carbon emissions and energy consumption from CO_2 transporter vehicles, and in turn, gross estimates of net CDR per this idealized scenario (see 2.6).

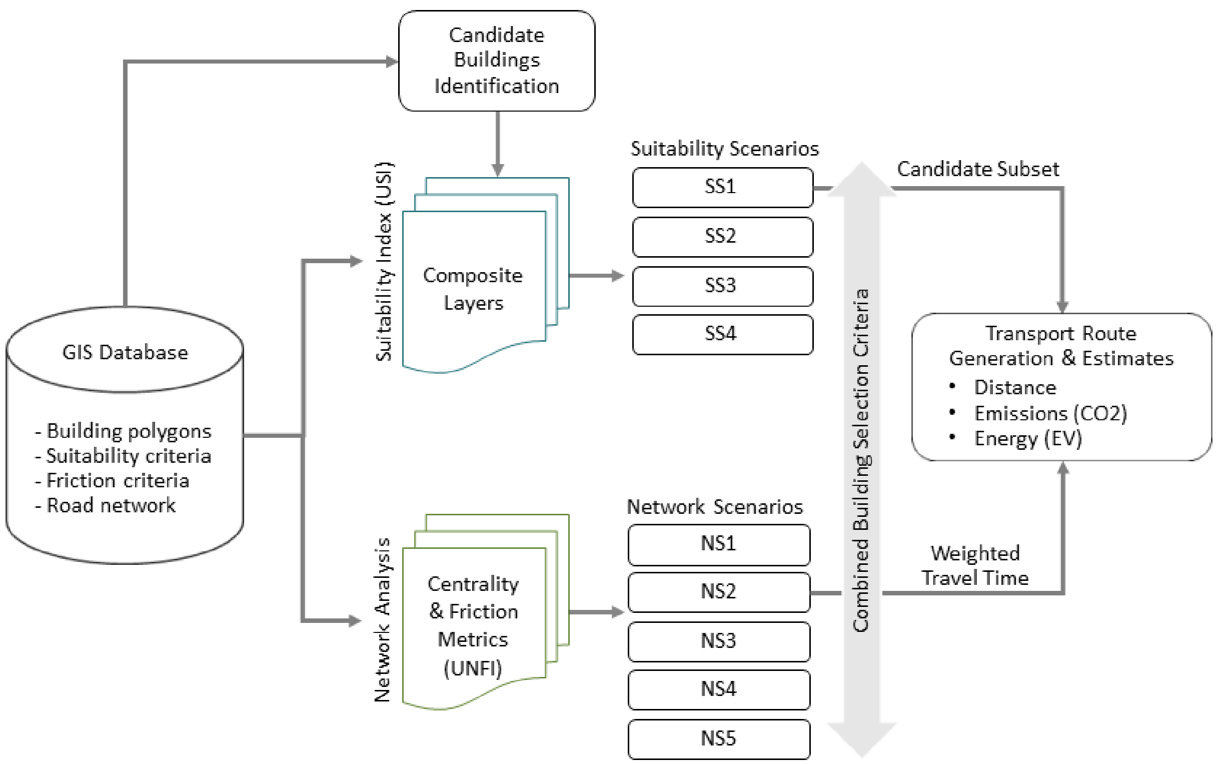


Figure 1. Graphical abstract of the methodology and preliminary results of MCDA framework for distributed UrbanDAC systems.

2.2 IDENTIFICATION OF CANDIDATE BUILDINGS

Due to data limitations, the first challenge to address is identifying existing building stock likely to have cooling systems amenable to UrbanDAC adaptation based on our technology use-case (i.e., individual cooling tower-adaptable DAC units). While datasets with attributes specific to UrbanDAC are currently unavailable for our use-case (e.g., has a cooling tower), several options exist for building footprints datasets from which it is possible to estimate proxy attributes, including Open Street Map (OSM). To this end, ORNL's USA Structures [20] dataset is preferred due to its completeness, reliability, and documentation.

Given that the target buildings would have certain attributes pertaining to the need for a mounted cooling tower beyond the HVAC systems typical of other building classes (e.g., residential), we assume that buildings that are designated as commercial and are relatively large in terms of floorspace can be potential candidates. To determine selection criteria, EIA's Commercial Buildings Energy Consumption Survey (CBECS) [21] offers guidelines for designation of commercial buildings. Based on these guidelines, the first step is to select USA Structures footprints within City of Knoxville boundaries using Geographic Information Systems (GIS) that have a height greater than 1 story (3m) and more than $93m^2$ ($1000ft^2$) in floorspace. USA Structures includes height and footprint area attributes for each record that can be easily used to calculate the floorspace for each structure. The selected buildings are then further selected according to planning zones amenable to commercial building uses. Geographically explicit planning zones are available from the City of Knoxville GIS portal (KGIS) [22], [23] as a shapefile, which was used to subsequently select structures that spatially overlay specific zones that allow the target building types (see Table 1 below).

Table 1. City planning zones used as selection criteria for candidate buildings [23].

Zoning Code	Description
C-G	General Commercial
C-H	Highway Commercial
C-R	Regional Commercial
OP	Office Park
I-RD	Large-scale Office & R&D
I-G	General Industrial
I-H	Heavy Industrial
INST	Institutional
TO-1	Technology Park Overlay

2.3 DECISION VARIABLES & DATA

Parameters for optimal UrbanDAC performance were framed around (1) *resilience* in terms of route redundancy and minimizing UrbanDAC service disruptions, and (2) *sustainability* in terms of the energy efficiency of the overall system of distributed carbon capture and transport. Subsequently, parameters were selected based on factors that would either decrease the performance or cause a disruption of a small-scale DAC unit (e.g., failure of a building's cooling tower system), or add *friction* to the network by decreasing the efficiency of the transportation network or having few alternate routes.

A variety of applicable datasets to inform these factors are publicly available in geospatial datahubs from governmental and non-governmental sources. The variables selected for this study, the respective reasoning, and associated data sources are listed in Table 2. These variables were meant to inform a working concept, so this list is not exhaustive, and several studies are needed to determine an optimal set of variables. Additionally, several hazards were not considered, such as earthquakes and interdependent infrastructure like electrical power networks. We chose flooding due to its prevalence across many urban geographies and applicability as a test-case for further development.

Table 2. Parameters (variables) selected for initial UrbanDAC assessment and network analysis.

Parameter	Description/Reasoning	Data Source & Vintage
Building Density	Degree to which areas represent concentrations of larger buildings. Greater densities can reduce system consumption (e.g., excessive collection site disparities; cumulative distance traveled). Building density can be derived from USA Structures footprints and attributes.	USA Structures 2022 [20]
Distance to Nearest Rail Station	Assuming rail stations and carbon transportation hubs, closer buildings are optimal for system efficiency. The distance to these stations can be computed as a Euclidean surface.	OSM 2022 [24]
Flood Risk	Flood risk zones indicate the probability of flood-induced impacts such as power outages, road delays, and out of service buildings. These zones can be quantitatively classified according to risk level.	FEMA 2018 [25]
Precipitation	Precipitation reduces the airborne concentration of CO_2 and increases road wear. PRISM offers downscaled modeled datasets at 800m spatial resolutions for 30-yr precipitation normals (1991-2020).	PRISM 2020 [26]
Traffic	Annual traffic station counts can be used to develop spatial density surfaces along roadways that indicate areas of increased lag, energy use, and emissions.	TDOT 2020 [27]

2.4 GEOSPATIAL SUITABILITY ANALYSIS

Geographic optimization can reduce cumulative costs and resource consumption relative to carbon capture performance across urban systems and streamline the process of implementing a distributed DAC system. The objective of the geospatial suitability analysis was to locate optimal candidate buildings such that their cumulative distribution for UrbanDAC systems maximize cumulative performance, particularly carbon capture efficiency, by leveraging spatially explicit data outlined in section 2.3. The methodology for the suitability analysis process is summarized in Figure 2.

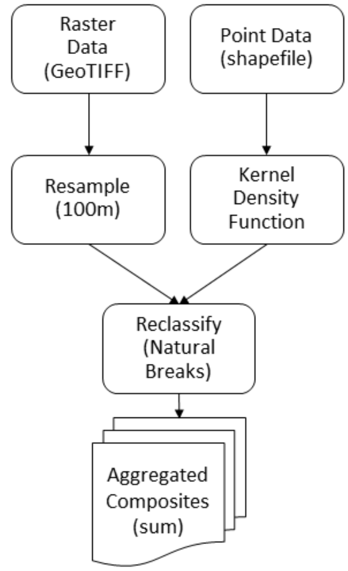


Figure 2. Geospatial workflow for suitability analysis.

The development of suitability scenarios involves integrating spatial data on carbon capture potential (e.g., atmospheric conditions, DAC performance) and building attributes (e.g., building footprints, zoning). We develop decision analytics based on (1) performance factors, including building density, precipitation, and distance to rail stations, and (2) risk factors, which were represented by flood risk level. To do this, we use a common form of geospatial MCDA technique [28], [29] where the data distributions of each variable (C_j) is classified into a common rank ordered score according to desirability, weighted (W_j), then spatially summed to produce a composite map highlighting high return to low return areas:

$$A_i = \sum_{i}^{n} (C_j)(W_j) \qquad (1)$$

The aggregate score A_i represents the scenario composed of a given selection of decision variables and their weight. As a pilot study, we assume that all $W_j = 1$ for this report. As explained below, variables were aggregated via raster calculations for geographically heterogeneous digital surfaces representing each of the decision variables for Knoxville. To develop commensurate digital surfaces from point-based data, *Kernel Density Estimates (KDE)* were performed at 100m grid-cell resolution for each variable and with kernel sizes used to generate estimates optimized according to Simpson's rule [30]. The KDE process transforms discrete vector data into continuous rasterized surfaces (i.e., pixels). In the case of building density, the KDE algorithm uses floorspace as a weight for each data point in the kernels to capture the spatial variation in the scale and clustering of commercial buildings eligible for UrbanDAC. Datasets already in raster format were resampled to 100m resolution, if necessary, using a cubic convolutional method of interpolation [31], [32].

The last step before applying the MCDA equation for aggregation is to reclassify each dataset into categorized scores in integer increments from 1 to 5, where a score of 1 represents the least suitable areas and a score of 5 the most suitable areas. To segment the data into these scores, a *natural breaks* algorithm was applied since it subsets records into groups with more distant means, and thus better contrasting the suitability of different areas for greater facilitation in decision-making. Once reclassified, the datasets are aggregated using an arithmetic sum and assuming equal weights in the scenarios in Table 3.

Table 3. Suitability scenarios and criteria for geospatial suitability analysis with corresponding network criteria for urban scenarios.

Suitability Scenario ID (SS)	Criteria	Corresponding Network Scenarios (Table 4)
1	Building Density	1-5
2	Building Density, rail	1-5
3	Building Density, rail, flood zone	2, 3, 5
4	Building Density, rail, food zone, precipitation	2

2.5 NETWORK ANALYSIS

2.5.1 Quantification of Accessibility to Identify Key Building Nodes

Access to multiple alternate routes increases the resilience of any point of interest (POI) that is reachable through a network (e.g., a road network). We developed a method based on the accessibility of buildings to rank the candidate buildings, maximize the resilience of the UrbanDAC system and optimize the collection process. From an interdisciplinary engineering perspective, resilience generally speaks to the ability of a system to adapt to changes expediently to decrease total recovery costs and the length of service disruptions [33], [34]. Network topologies play a key role in urban resilience [17], [35]. For example, nodes with a higher centrality are more flexible and agile during any unexpected events as such nodes are more accessible through several alternate routes. Therefore, vulnerability of any critical POI (e.g., an UrbanDAC unit) can be reduced significantly if they are connected to more central nodes in the road network. Following a network science approach enabled metrics that inform compromised transportation performance scenarios, such as removing a road segment or a set of road segments due to events like natural hazards.

The primary objective of the network analysis was to evaluate candidate buildings as nodes integrated into the road network while considering factors such as distance, edge weights, and the minimization of disruptions and costs associated with carbon transportation. First, we downloaded the drivable road network from OpenStreetMap as a graph and simplified the graph by removing all the nodes except for the junctions using the Python OSMnx package [36], where junctions are the intersections of roads. We then connected the candidate buildings to the nearest road junction to integrate the buildings into the road network. Finally, the accessibility of those candidate buildings in the road network were estimated using node betweenness centrality. We chose betweenness centrality as it is a crucial network metric that measures how many shortest paths in a road network pass through a node; therefore, it best captures the accessibility of each building through the road network. Betweenness centrality of a node v is the sum of the fraction of all pairs of shortest paths that pass-through v. Thus, betweenness centrality (cB) of a node v is,

$$c_B(v) = \sum_{s,t \in v} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{2}$$

where, v is the set of nodes, σ(s,t) is the shortest paths between all source-target pairs, and σ(s,t|v) is the number of those paths passing through edge [37], [38]. We used the Python Networkx package [39] to estimate the betweenness centrality of the road junctions in Knoxville. This metric has been applied in various domains, such as social network analysis, infrastructure protection, and network resilience assessments [40]–[42]. Nodes with high betweenness centrality control information flow and resource distribution within networks [37]. As buildings are sink points in the network where a path ends, thus, they do not have any betweenness centrality as no paths pass through them. Therefore, in this study, we estimated the accessibility of a building as the average betweenness centrality of all the junctions within a kilometer of driving distance from each building. Buildings with high accessibility act as pivotal points in the transportation network, being resilient and facilitating the flow of CO_2 from the capturing units to storage or processing facilities.

We included various factors as edge weights to estimate the accessibility of UrbanDAC units under different scenarios of unequally distributed network friction (see Table 4). For example, the traffic layer is used to assign traffic information as edge weights to the road network and modulate betweenness centrality metrics. For this study we used three friction factors: traffic, on-road precipitation, and flood risk level to develop three scenarios of ranking for each UrbanDAC unit. Each one of these individual friction factors resembles one network scenario for selecting critical buildings. However, two additional combinatorial scenarios were simulated: one scenario considering both flooding and excessive precipitation, and one considering all three (traffic, precipitation, flood risk). To combine factors, we followed the geospatial MCDA approach described in equation 1 in section 2.4 (Table 4).

Table 4. Network friction scenarios and criteria with corresponding building-level suitability for urban scenarios.

Network Scenario ID (NS)	Criteria	Corresponding Suitability Inputs (Table 3)
1	Flood	1-2
2	Traffic	1-4
3	Precipitation	1-3
4	Flood, precipitation	1-2
5	Flood, Traffic, precipitation	1-3

2.5.2 Urban Routing Scenario for CO_2 Transport in UrbanDAC Systems

To make calculations for the total distance traveled and estimate emissions and energy use for CO_2 transport, potential routes from the storage hub to each building housing UrbanDAC units needed to be generated. These generated routes act as synthetic data for estimating system-level metrics for a typical fleet of CO_2-Transporting Vehicles (CTV; such as "AirGas" trucks carrying pressurized tanks), and in-turn, operational impacts to net CDR according to the idealized scenarios described in this report (*see* 2.6 and 3.3). We applied a network optimization function while taking on a few assumptions for simplification and reduction of compute time:

i. The decision variable refers to the alternative with minimal total distance such that each node (i.e., building) is passed at least once.

ii. All links in the transportation system represent bidirectional rights of way.

iii. CTVs begin and end at the rail station nearest to a candidate building.

iv. The CTVs travel in a circular route with a single pickup from building to building (i.e., they do not intentionally return to a building).

v. The simulation was limited to a subset (*see 2*.6) of the candidates identified in section 2.2.

The subset of candidate buildings was selected by rank ordering candidates according to a combination of USI and UNFI scenarios focused on building density and travel time as primary decision factors, respectively. From this scenario we selected the 20 highest scoring buildings (i.e., those inhabiting and surrounding areas that have relatively high floorspaces and incur low traffic delays in respect to intermediate and endpoints). Ultimately, determining an idealized route for this set serves as a baseline for an urban scenario where carbon is captured at the building-level (i.e., UrbanDAC), picked up via motorized vehicles and transported to the nearest rail hub.

2.6 HIGH-LEVEL URBAN SCENARIO ASSESSMENT

The urban scenario in this report represents a system-level assessment for envisioned UrbanDAC deployment strategies using combinations of selected parameters and outputs from the methods described in previous sections. The geospatial analysis results mapped candidate locations distributed among the buildings in Knoxville. The analysis also indexed these candidates according to alternative decision criteria and composite suitability score based on scenarios reflecting flood risk, precipitation, building density, and distance to nearest rail station as parameters. Using these results, an illustrative USI-UNFI combinatorial scenario was used to identify optimal building candidates and observe how these candidates change based on different index combinations. The twenty highest scoring candidates for building density were selected from the suitability analysis (i.e., SS1 in Table 3). In turn, this subset was used to select the five highest ranking candidates according to betweenness centrality under a series of network friction parameters (Table 4). This combinatorial scenario was used to assess the spatial variation in optimal building selection strategies for UrbanDAC.

The "top 20" subset was also used to generate a pick-up route (*see* 2.5.2) for an idealized carbon transporting vehicle (CTV) and calculate total travel, emissions, and energy outcomes. To determine an appropriate vehicle type, we focused on commercial vehicles with the minimal capacity to transport at least 1300 kg, assuming a weight of 62 kg per empty 50-liter pressurized tank [43] plus the weight of captured carbon (1 kg) from each site (62 kg tanks x 20 buildings + 20 kg CO2 = 1300 kg). These are rudimentary assumptions since several factors may affect outcomes, such as the kg-CO_2 capacity of a tank depending pressure, here assumed to be 1 bar based on the Ideal Gas Law and ratings of commercial products, and therefore, there would be 1 tank per pick-up.

To make baseline estimations, we used the length of the route to calculate course estimations of the emissions and energy consumption for this UrbanDAC scenario. For emissions data, we leveraged a study by Weiss et al. [44] estimating the average per-kilometer CO_2 emissions for small commercial transporter vehicles with two axles (e.g., "AirGas" trucks transporting typical pressurized gas tanks up to 50 liters each; N1/Class II Euro 3). For energy consumption metrics, we estimate the total watt-hours consumed using data from ERM International group's study on environmental impacts of medium and heavy-duty vehicles [45]. The report cites 0.74 kWh/km (1.19 kWh/mi) on average for medium duty commercial vehicles such as service vans and stake trucks within a weight Class 3-5.

The aim of this methodology was to capture and assess broad-level impacts of an interconnected urban system composed of DAC-enabled buildings and urban thoroughfares. These impacts were assessed using the above urban deployment scenario to make rudimentary distance, CO_2 emissions, and energy consumption estimations for an UrbanDAC system. However, the combination of parameters and selection criteria used here represent just one series of possible deployment scenarios, though several alternative strategies can be assessed in future studies based on this data and framework. Furthermore, many of the outputs of this initial assessment, such as the optimized subset of candidates and respectively generated transport route, cue further study and modeling of the datasets of both alternative scenarios and multiple scales of deployment.

3. RESULTS

Results in this report include the identification of candidate buildings in Knoxville, multi-criteria suitability mapping, and a network analysis that assigns a score to buildings according to their betweenness centrality, as well as scenario-driven route generation. These three components yielded three major products: (1) a working UrbanDAC Suitability Index (USI) for the City of Knoxville, (2) an UrbanDAC Network Friction Index (UNFI) for the City of Knoxville, and (3) commercial building rankings by selected deployment scenarios (4) rudimentary summary statistics for transportation impacts. Of the 68,306 buildings from the original USA Structures dataset, the identification process outlined in section 2.2 selected a total of 4,562 buildings (~7%) to be designated as commercial buildings viable for UrbanDAC system adaptations (Fig. 3). Individual building floorspace varied from 92 m^2 to 262,814m^2, with a total of 12,472,863m^2 estimated in floorspace for the UrbanDAC-identified buildings. Major building clusters by floorspace-weighted density surfaces are generally intuitive to areas of larger-scale development, such as the University of Tennessee campus and primary technology and shopping districts. A 43.1 km route was generated for a "top 20" buildings scenario that implies a transportation impact of 8 kg in CO_2 emissions or 31.9 kWh of EV energy per round. Below we summarize results in greater detail according to the three components of the study: the geospatial suitability analysis, the network analysis, and the final MCDA for integrated urban scenarios.

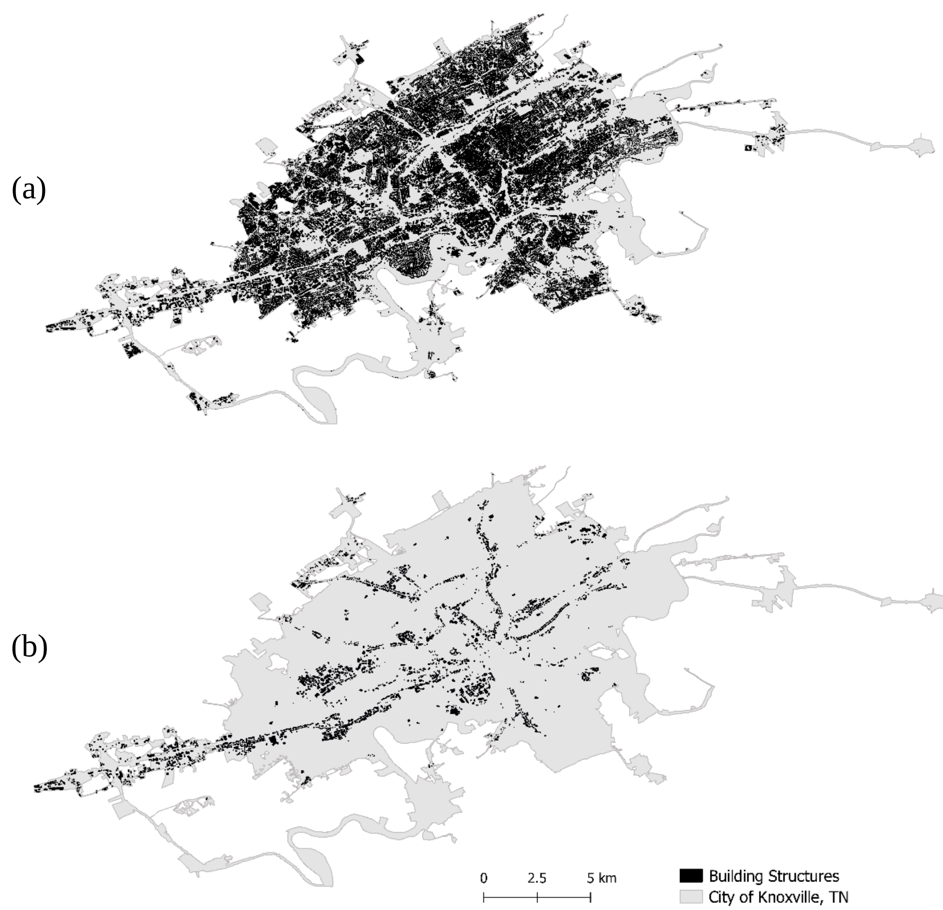


Figure 3. The top figure (a) shows USA Structures building footprints for Knoxville, TN. The bottom (b) figure shows the USA Structures building footprints after selection for UrbanDAC commercial building criteria. In both cases, the building footprints are shown in black.

3.1 GEOSPATIAL SUITABILITY FOR URBANDAC DEPLOYMENT

The main products from the geospatial analysis are the suitability maps and geographic visualizations that mark urban areas for UrbanDAC system implementation and modeling scenarios for further research. Final outputs include scenario-based indices and ranked candidate buildings that were developed to illustrate how UrbanDAC may be distributed in a mid-sized city like Knoxville. For example, Figure 4 represents the most comprehensive scenario (SS4, see Table 3). In this scenario, to demonstrate optimal areas for UrbanDAC siting based on flooding, distance to rail stations, precipitation and road density, areas throughout the city ranged from a composite score of 5 to 19.

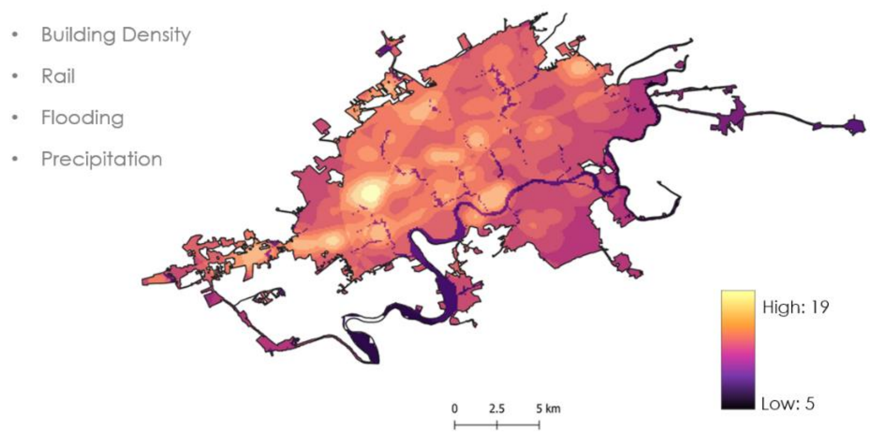


Figure 4. Preliminary suitability index for distributed UrbanDAC units in Knoxville, TN. Higher scores trend toward yellow while lower scores toward dark purple.

Because there are essentially four scenarios where an increasing number of variables are reclassified as integers from 1-5 to be aggregated as a composite, the ranges vary respectively, though not always to the full minimum and maximums of each range. For instance, the suitability scores that include only building density and the radial distance to rail range from a score of 3 to a score of 10 (Fig. 5). Generally, the yellow and bright orange areas in the map represent clusters of university buildings and general industrial districts. It is also noticeable between Figures 4 and 5 that additional variables attenuate such highly contrasting regions in the West and Center of town, making results more nuanced once 3 or more siting parameters are considered. Once precipitation and flooding are considered, for example, the Western industrial cluster is now differentiated and favored in respect to the university district, despite the latter having high building density and being closer to the transportation hub (i.e., rail station).

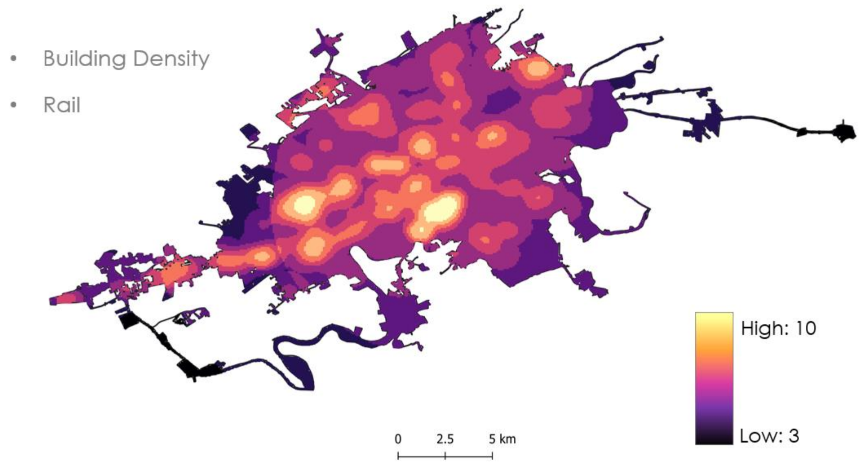


Figure 5. Preliminary USI scenario considering only building density and distance to rail stations. Higher scores trend toward yellow while lower scores toward dark purple.

Nearly half (47.9%) of the identified candidates were within a half kilometer of a floodplain, with 126 buildings inside floodplain areas designated by FEMA. Buildings located directly or nearby such high flood-risk areas, as well as within a half kilometer range of currently 100-year flood risk areas (*N = 399*) suggest further research is needed, especially considering potential changes in climate, land-use, and at finer resolutions to properly identify buildings at risk. Implications due to resolution also resulted from the PRISM dataset being downscaled from climate model outputs. The precipitation data is stratified in thick bands with higher values in the West with a lowering gradient toward the East, which is especially observable in the reclassified layer and sometimes evident in the scenario composites (see Appendix A). Therefore, despite PRISM's finer resolution in respect to global-scale data (800m), it is possible that there may be greater spatial variation in precipitation within the extent bounding Knoxville, TN, that can be captured at smaller scales (e.g., 500m or finer).

3.2 NETWORK ANALYSIS & CO_2 TRANSPORT ROUTING

3.2.1 UrbanDAC Network Friction Index (UNFI)

A series of UrbanDAC Network friction indices (UNFI) were developed to represent transportation conditions where a reduction in efficiency or risk of disruptions result in greater systems-level energy and operational costs. Using the geospatial methodology from section 2.4, a set of composites were created using variables specific to network scenarios (traffic counts, precipitation, and flooding). These composites were then used to spatially assign friction metrics to individual edges of the network (i.e., road segments). Figure 6 shows the resulting transportation network friction results based on traffic count density. It is observable from the figure that there is greater friction surrounding the center of town (downtown, University of Tennessee, Old City leisure district) and a major shopping district (Turkey Creek) to the West. Further results from the UNFI are discussed in terms of centrality metrics in 3.2.2. and candidate building selection and routing in section 3.3.

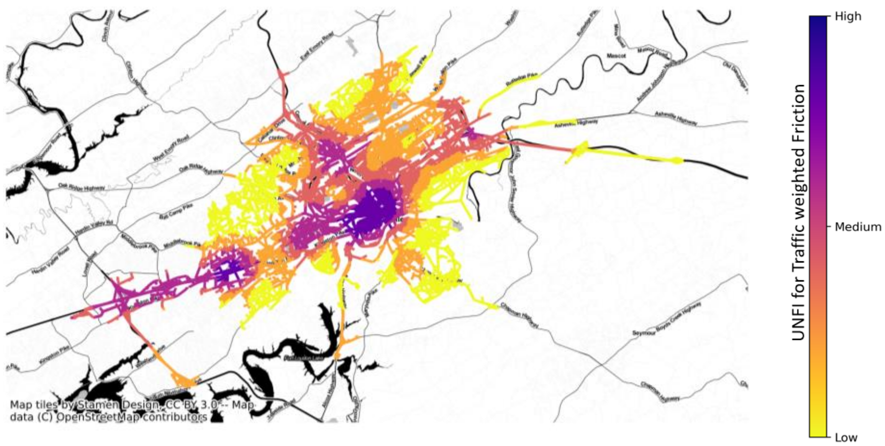


Figure 6. UrbanDAC Network Friction Index (UNFI) for Knoxville, TN. The more purple colors display higher friction areas of the road network, while more yellowish colors define the lower friction edges.

3.2.2 Betweenness Centrality by UNFI Scenario

Betweenness centrality metrics were calculated for each building by UNFI scenario. Figure7 shows the node betweenness centrality of an illustrative set of UrbanDAC units for a UNFI under floodplain and traffic conditions in Knoxville, TN. Higher values indicate higher accessibility weighted by either flooding or traffic, which can be used to rank and prioritize the potential locations of UrbanDAC units. Our initial analysis suggests commercial buildings in Northeast Knoxville should have a higher priority as locations for resilient UrbanDAC units, considering both flood and traffic congestion simultaneously. However, while the Northeast tends to suffer less traffic and flood risk, the top-ranking units result from the West and South of Knoxville due to higher accessibility.

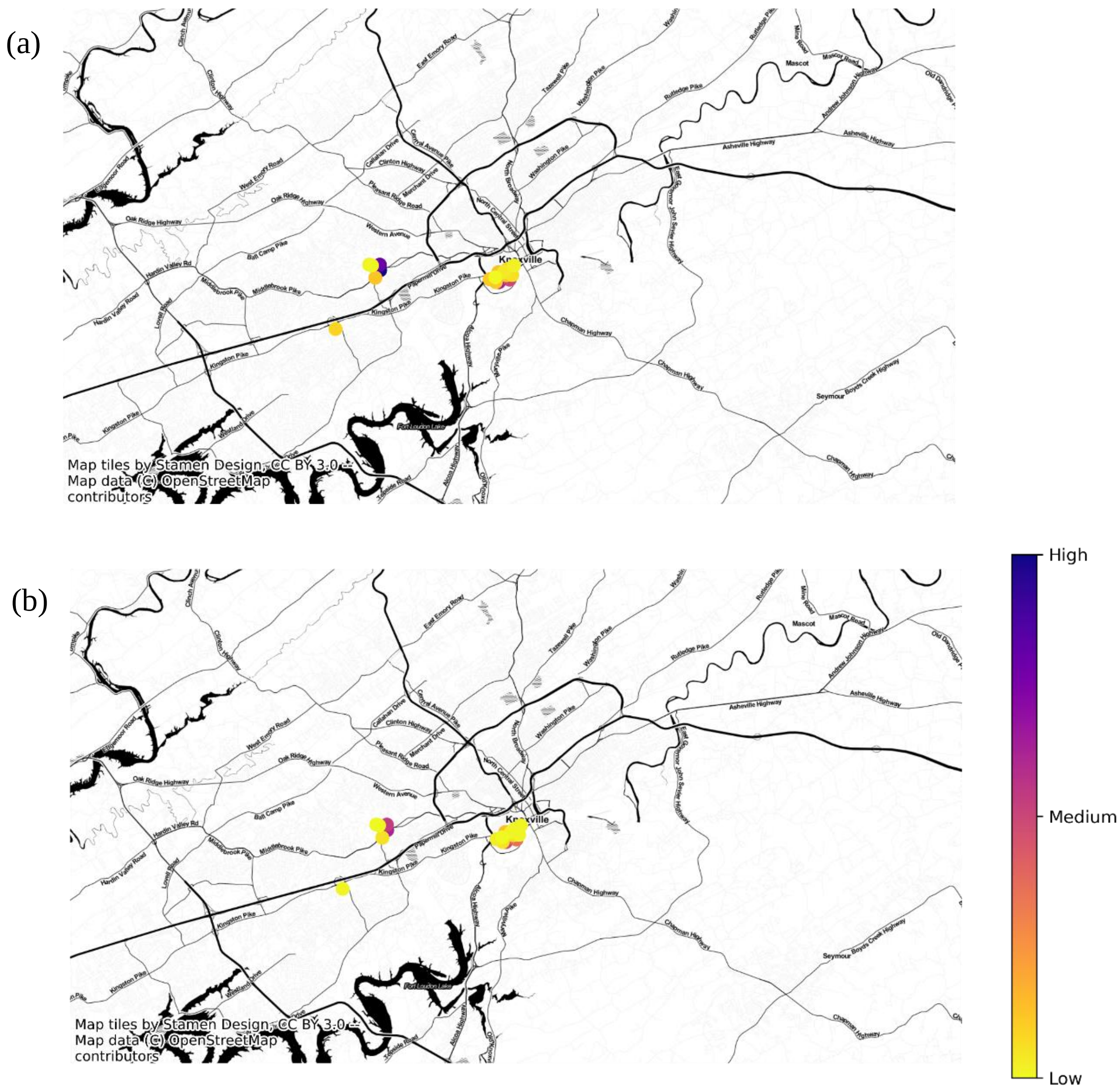


Figure 7. Node betweenness centrality for distributed UrbanDAC scenarios in Knoxville, TN, assuming (a) flood risk and (b) traffic as network friction parameters. Each point represents the location and weighted centrality of commercial buildings where from yellow to purple suggests lower to higher efficiency and resilience, respectively.

3.3 HIGH-LEVEL INTEGRATED URBAN SCENARIO ASSESSMENT

At the macro-level, the urban scenario was defined by a set of proposed infrastructure systems that could hypothetically be implemented (e.g., to achieve decarbonization goals by 2030), the selected characteristics of these systems, and environmental conditions. The proposed infrastructure system is composed of high-density commercial areas (i.e., built environment with buildings as decarbonization infrastructure), vehicle-oriented transportation of carbon products, and rail stations as regional hubs. Together with connectors and highways, the rail stations form a hierarchical transportation network for centralized storage and processing at greater scales. However, within the scope of this study, we treated the rail stations as the city-level endpoints. A total of two rail stations were identified within the Knoxville boundaries, which were located near the center of the city and South Knoxville. The main characteristics of the infrastructure systems include building density, traffic counts, and betweenness of building locations in the road network. For the environmental conditions, we consider precipitation and flooding.

Among these variables, there are a variety of combinatorial scenarios for USI and UNFI and levels of comprehensiveness for integrated analysis, from which we highlight a selection. Depending on the criteria used for the USI and UNFI, the locations of the top-scoring buildings change, as demonstrated in Figure 8. However, these locations tend to be fixed consistently within neighborhood-level clusters and change mainly in terms of ranking. There are a few exceptions where locations shift between the primary clusters, however, particularly between candidates that switch between the West Knoxville and University of Tennessee clusters, two areas with relatively very high building densities and generally higher ranking UNFIs. This observation suggests that planning decisions for UrbanDAC may involve important considerations in terms of spatial variation for optimal candidates within thriving commercial areas of the City.

To assess the distribution of building candidates as an integrated urban scenario, outputs from the suitability analysis were used as inputs and constraints for the network analysis, following the same methods covered in section 2. First, the twenty highest ranked candidate buildings were selected according to the suitability analysis for the simplest scenario (SS1; building density only) and their betweenness centrality metrics. Using this combination of land suitability and network criteria, a data-driven selection of candidates was identified as key buildings that play a critical role in the efficient transportation of captured CO_2, minimizing both energy consumption and disruptions of decarbonization infrastructure.

An optimized route was generated from these top 20 candidates using building density and traffic as the USI and UNFI criteria, respectively. While this may exclude relatively high-suitability buildings along or near this route, we considered this an illustrative scenario based on selecting the simplest set of criteria while retaining two salient factors in terms of floorspace as a proxy for UrbanDAC unit capacity and travel time as a key transportation concern. A single loop was assumed where the rail station nearest to the first building were the begin and endpoints for a single vehicle to travel through the network stopping at each of the selected buildings. The resulting route was calculated to have a total of 43.1 km in distance traveled for a single round (Fig. 9).

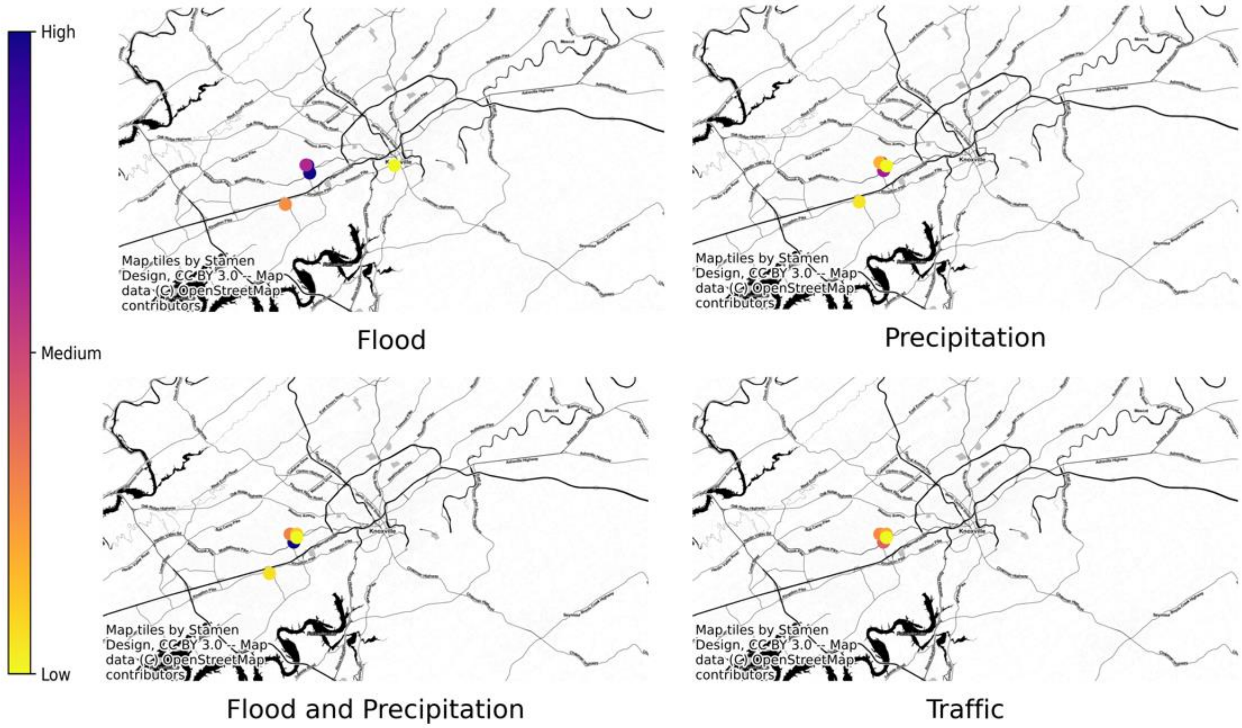


Figure 8. Top 5 highest ranked candidate building locations based on building density-oriented suitability and different network friction criteria including flood risk, precipitation, flooding and precipitation, and traffic.

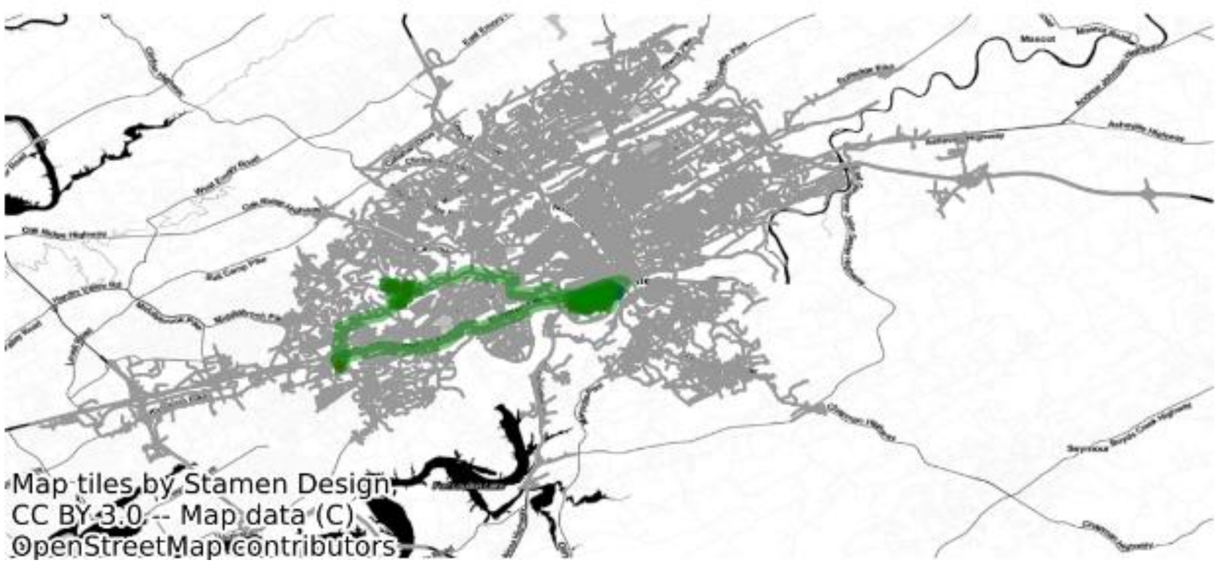


Figure 9. Optimized pick-up route for top 20 ranked candidate buildings according to building density and traffic USI-UNFI Combination.

Using 182 g CO_2/km as the average carbon dioxide emissions for the CTV scenario in section 2.6 [44], we estimated a total of 8 kg CO_2 in transport emissions per pick-up cycle. Given we assume an emerging DAC technology with an expected CDR rate of 1 kg CO_2/day and that each identified building candidate can house one unit, we assume a system-level DAC-unit CDR rate of 20 kg CO_2/day. The net CDR rate, however, is highly dependent on pick-up rate in terms of the emissions cost of CO_2 transport (Fig. 10). Depending on whether a unit renewal and CO_2 transfer is needed on a daily, weekly, or other frequency, the impact of transportation to the net CDR efficiency of this system varies, starting from a 40% of reduction of gross CDR capture assuming daily pickups (12 kg net CO_2 for per day) to near 0% for annual. Given that the efficiency of our transportation scenario increases in a logarithmic fashion, schedules with weekly pickups or less frequently approach very low transportation impacts under these assumptions.

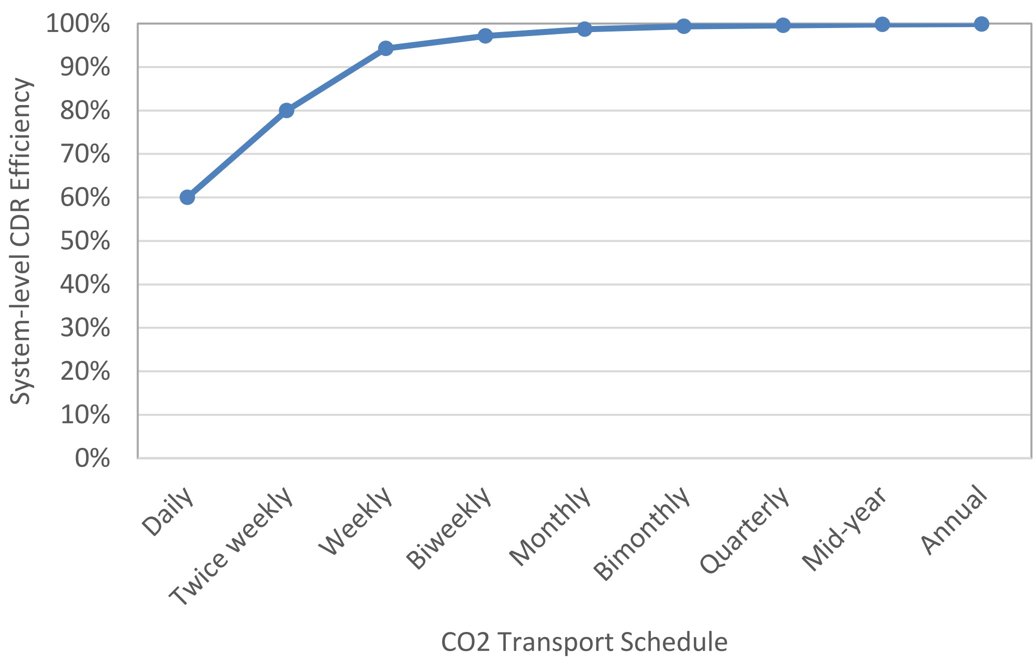


Figure 10. The efficiency of carbon dioxide removal (Gross CDR – Transport CO_2) for the urban scenario involving a 20-stop route at different rates of pick-up schedules.

In terms of energy consumption for an EV scenario, we assumed a vehicle efficiency of 0.74 kWh/km based on the average of the vehicles determined in section 2.6 [45]. This energy consumption rate translated to a total of about 31.9 kWh for a single round. Generally, the energy storage required for a single round is well within the typical travel range and battery capacity for small transporter EVs [46], [47]. We considered energy consumption in the EV scenario as a measured outcome of the scenarios we explored in this report, and due to scope, did not further explore interrelationships, outcomes, and dynamics in respect to other system components (e.g., grid distribution, charging stations, etc.). Therefore, in terms of multiple rounds in the case of scheduling, energy demand for captured CO_2 transport will also vary greatly in respect to the pick-up schedule required, but in a more straightforward linear fashion (i.e., multiplicative increases with higher frequencies).

4. CONCLUSION & DISCUSSION

4.1 SUMMARY

In conclusion, a data-driven framework was piloted as an approach to assess and optimize the siting of adaptable UrbanDAC units, minimize service disruptions, and enhance the overall sustainability and resilience of UrbanDAC for carbon dioxide removal. Through the application of geospatial and network analyses, eligible buildings for DAC adaptation were identified, subsequent candidates were ranked in terms of optimal spatial and network locations, and preliminary routes were generated for selected urban scenarios for UrbanDAC implementation. The identification process selected a total of 4,562 buildings (~7% of the 68,306 buildings from the original dataset) as viable candidates for UrbanDAC system adaptations. Major building clusters with top ranking candidates were found to align intuitively with areas of higher building density and larger-scale development, such as the University of Tennessee campus near the city center and primary industrial and shopping districts, largely on the West side. However, there is spatial variation in terms of suitability and network characteristics within and between these major clusters, and the respective locations of some top rankings (e.g., top 5 in urban scenario) are sensitive to weighting and selection criteria (i.e., may switch locations within or between major clusters). These insights represent useful considerations for identifying strategic areas for UrbanDAC planning and deployment and achieving the greatest carbon capture potential at the systems-level.

As an integrated scenario, a representative subset of high-ranking UrbanDAC candidates were used to generate a 43.1 km route that loops between the nearest rail station and each building in the subset ($N = 20$). In terms of energy impacts for this scenario, results suggest that transportation of UrbanDAC products (i.e., captured CO_2) may incur about 8 kg in fuel-related CO_2 emissions and 31.9 kWh of EV-energy impacts per pick-up cycle. For a subset of twenty high-ranking candidate buildings, this study suggests a net CDR rate of 12 kg for daily pick-ups to near 20 kg per day for annual pick-ups, depending on pickup schedules. However, these results represent rudimentary calculations for CDR efficiency. It is possible, for example, that there are several favorable buildings along the same route generated for the subset ($N = 20$) presented here, and therefore, economies of scale need to be assessed and modeled. Results also suggest scale-based implications for further analysis of microclimatic factors in terms of local precipitation and more granular flood risk data. Furthermore, there are several other CO_2 and energy-related costs that need to be considered for improved net CDR quantification, such as the life cycle of the DAC units, variable performance, and operational dynamics.

Results from this study, including the identification of a significant number of buildings suitable for UrbanDAC, provide valuable insights for decision-making processes and serve as a foundation for future urban-scale studies of DAC systems, aiding in the transformational decarbonization of cities. The proposed concept and methodology can be expanded to other cities and regions, both domestically and internationally, enabling the assessment and comparison of different configurations and distributions of DAC units within urban environments. The first challenge is identifying candidate buildings and characterizing their distribution (e.g., scale and extent of clusters) in terms of captured CO_2 transportation and storage. The next step is leveraging the network of identified buildings to assess economies of scale and alternative system configurations using system-level metrics (e.g., cumulative energy demand for EV vehicles or pumps along a pipeline; net lifecycle CDR) and quantitative decision metrics (e.g., maximize cumulative CO_2 performance, lower energy impacts, etc.). For this, reliable data on building attributes, transportation and other urban networks, and other local attributes are fundamental. Further research can aim to create a database of metrics grounded in an UrbanDAC framework to address current gaps in literature that can draw from this framework replicated in other cities. Interdisciplinary research can significantly enable stakeholder-driven tool-building for UrbanDAC implementation and management, and deployment of monitored pilot projects as living experiments of UrbanDAC best practices.

4.2 LIMITATIONS & FUTURE WORK

Building on preliminary results and collaboration with the broader Transformational Decarbonization Initiative (TDI) at ORNL, this study has laid a foundation for future studies of urban-scale DAC systems, here termed UrbanDAC. One overarching aim of this work was to initiate essential first-order calculations that shed light on the potential city-level impacts of distributed DAC and the relative efficiency of such a system given the necessary systematic costs, energy demands, and environmental impacts. Central to this work is the creation of idealized scenarios based on living cities and neighborhoods to enable practical estimations, "real world" illustrations, and local applicability for urban climate change mitigation goals. Considering a set of preliminary natural and built environment factors enables the computation of aggregate UrbanDAC impacts and assessment of the feasibility of different configurations in an urban space.

It is worth noting that several attributes beyond location, such as building occupancy, building capacity for multiple UrbanDAC units, and variance in DAC unit carbon capture rates, can be integrated into the analysis, providing a more detailed understanding of the system. This is also true for additional transport-related impacts such as NOx and particulate matter emissions. Furthermore, future modeling and simulation studies can better capture the complexity of an integrated UrbanDAC system by including city-level interactions such as building use, mobility, and other relevant urban dynamics.

While this report focused on one potential strategy among several alternatives, the goal was to pilot a comprehensive decision-making framework that incorporates various planning-relevant criteria. At a high level, future work can build on this approach to explore alternative scenarios for UrbanDAC infrastructure. Whereas this study posited UrbanDAC transport and storage via road vehicle transport with railways as a local hub, alternative high-level infrastructure configurations and logistics can be envisioned, including those based on district pipeline networks, industrial systems (e.g., manufacturing), or carbon storage facilities with varying degrees of centralization [14]. Analyzing the feasibility, cost-effectiveness, and environmental implications of these alternative scenarios can enable insights into optimized carbon transportation and storage strategies within an urban context, enhancing the overall CDR impact and sustainability of UrbanDAC systems.

In addition to alternative urban scenarios, there are several pathways to explore future research and development of the UrbanDAC concept and the methodology in this report:

1. ***Enhancing risk analysis and spatial calculations:*** This includes incorporating additional variables like topography, meteorology, road conditions, and other relevant factors to improve the suitability and network layers, and advanced geo-computations such as network distance optimization to hubs and spatially weighted metrics. Baseline models can also be developed to calculate relative CDR and estimate system-level energy demands based on the number of carbon transport vehicles, different network characteristics, and travel times to explore different infrastructure configurations.

2. ***Incorporating detailed building information:*** With more detailed buildings data, the process for identification of eligible buildings to serve as UrbanDAC candidates can be refined. Attributes including use-type, energy estimates, and other variables can help locate and determine building-types suitable for UrbanDAC implementation. Integrating HVAC and cooling tower data can further improve candidate buildings identification, optimization, and enable more accurate CDR and cost estimations.

3. ***Techno-economic analysis and building-level modeling:*** Detailed cost estimates (e.g., \$/t CO_2) based on the number and distribution of UrbanDAC units were beyond the scope of this study. However, economies of scale are possible and market uptake for UrbanDAC need to be understood,

along with carbon-driven Life Cycle Assessments (LCA) of the mechanical units into the quantification of net CDR. Since UrbanDAC units depend on the performance of cooling towers and/or HVAC systems, building occupancy and usage can vary hourly, daily, and beyond, leaving a gap in understanding how CDR rates may fluctuate temporally and by building type.

Multi-sector dynamics and integrated assessment models: It is important to understand the infrastructure interdependencies that will be built-in as UrbanDAC systems are integrated with other infrastructure networks, particularly roads and building energy systems, to evaluate coupled-system dynamics. While interdependencies are inevitable, they can be proactively designed and managed [35], [48], [49] and have salient implications for sustainable urban development (e.g., changes in energy demands; mobility and access). The outcomes of this study can contribute to larger-scale models by offering aggregated metrics for distributed CDR feasibility. At regional and global scales, integrated assessment models can use UrbanDAC metrics as inputs to provide insights into CDR feasibility and impact, as well as model novel global scenarios where city-level mitigation efforts are considered.

By addressing these areas, UrbanDAC research can advance decision-making processes, guide systems-level design, and support the transformational decarbonization of cities (i.e., net-zero initiatives). While understanding the mechanical performance of novel DAC technologies at the unit-level is important, interdisciplinary research is needed to go beyond ad hoc building-level siting by framing UrbanDAC as interconnected, networked infrastructure subject to natural and built environment conditions. By synthesizing systems thinking and urban planning, this report aims to initiate a comprehensive decision-making framework that includes a wide range of factors that can be refined and weighted based on stakeholder needs.

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7. APPENDIX A

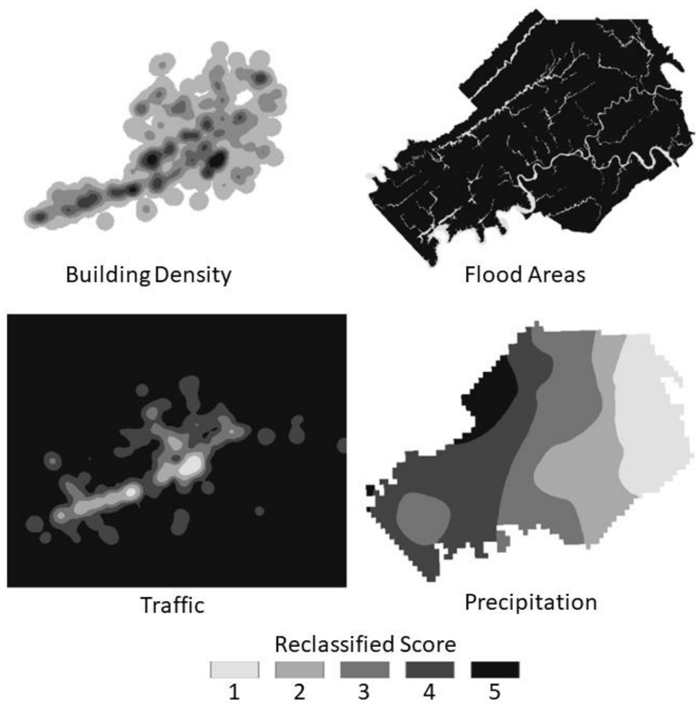

Figure X. Reclassified KDE surfaces for suitability criteria variables.