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Integrating sustainability indicators and governance structures via clustering analysis and multicriteria decision making for an urban agriculture network

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ABSTRACT

Environmental, social, and economic sustainability patterns interact in various dimensions of an urban environment. Exacerbated population growth triggers an emphasis on better resource management strategies addressing the balance of supply and demand over food, energy, and water sectors while considering social and economic development. Promoting sustainable development goals requires governance structures and functions within and across the food, energy, and water sectors, specifically due to polycentric urban development. This study emphasizes food security via an urban agriculture network in the greater Miami metropolitan area, encompassing the three counties of Palm-Beach, Broward, and Miami-Dade. Given the existing governance structure, we quantified several sustainability indices for clustering analysis to agglomerate urban agricultural sites (UASs) and to help identify the priority of clusters in terms of vulnerability or risk level according to their priority index in multicriteria decision-making. The cases of eight clusters were selected for the visualization of the UASs ranked by multicriteria decision-making based on scenarios prioritized for governance under the impacts of climate change, social equity, and economic development. The role of governance structure was highlighted for signifying the incentive programs to enhance the overall sustainability performance of UASs in an urban food–energy–water nexus.

1. Introduction

Urban complexity based on spatial scale varies as cities grow larger over time, with changes in urban morphology constrained by urban landscape. In developing countries, urbanization is often associated with economic development, thus promoting the increase of population density in cities (Shen et al., 2011). Hence, urban sprawl is expected to continue with 68 % of the world's population projected to reside in urban regions, for an additional 2.5 billion people in urban areas, by 2050 (United Nations [UN], 2018a). As such, the United Nations (UN) has established 17 UN Sustainable Development Goals (SDGs). Specifically, Goal 11 is aimed to make cities and human settlements inclusive, safe, resilient, and sustainable (UN, 2018a). It leads to achieve balanced social, economic, and environmental sustainability (Nikulina et al., 2018). Specifically, SDG Target 11.3 concentrates on inclusive and sustainable urbanization for sustainable planning and management (UN, 2018b). In congruence, the objective of the UN Food System Summit is to have an inclusive, sustainable, and resilient network, focusing on sustainable food systems as a necessity by bridging social, economic, and environmental sustainability development to promote autonomy and a circular economy (Nguyen, 2018).

Further, addressing climate change has become tied to urbanism and sustainability. According to the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6), human-induced climate change impacts can affect the frequency and intensity of heavy precipitation and extreme heatwaves, sea level rise, and droughts (IPCC, 2021). As such, policy instruments are important to establish and implement to achieve these sustainability goals at the intersection of urbanization, climate change, food security, and social equity, as in the case of the European Union (EU).

In the 2021 UN Climate Change Conference (COP26) it was expressed the urgency of approaching climate change with goals for decarbonization and global net-zero greenhouse gas emissions (GHG) (UKCOP26, 2021). The EU aims for carbon neutrality by 2050 by

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implementing a policy for this long-term objective. This strategy comes from the European Climate Law, part of the European Green Deal, which proposes net-zero GHG emissions for EU countries and carbon neutrality by 2050 (European Commission, 2020). However, to better understand sustainability, it is important to analyze a suite of sustainable indices and indicators to obtain a quantitative measure to assist in policy decision-making (Mayer, 2008; Mori & Christodoulou, 2012b).

The principles of urban sustainability entail sustainable metropolitan development in regard to social, economic, and environmental aspects (Radzi, 2018). This encompasses the understanding that a city transitions toward more green practices such as renewable energy. The National Academies of Sciences (2016a) explained that urban sustainability is a multiscale and multidimensional problem that includes the involvement of citizens and public and private entities while emphasizing the biophysical limits of the planet, interconnection of human and natural systems, urban inequality, and the interconnection of cities. Collectively, environmental, social, and economic sustainability interact in various dimensions. The implication of exacerbated population growth triggers concern for essential resource security, such as food availability, specifically in metropolitan regions. Food inequality also plays a role in different geographic regions based on food desert status. The U.S. Department of Agriculture (USDA) Economic Research Service recognized more than 6,500 food desert tracts in the 2000 Census and 2006 facts (Dutko et al., 2012). Moreover, Blanchard and Matthews (2007) noted the emergence of food deserts during the past 30 years as a result of the transition from small local grocery stores to supermarkets.

The USDA defines metropolitan areas as a food desert if the community has limited transportation resulting in low access to supermarkets or grocery stores and low income based on census tracts (Dutko et al., 2012). The Economic Research Service in USDA further defines a low-access community by having at least 33 % of the population or 500 people that live more than 1.6 km (1 mile) from supermarket or grocery store in an urban region. The 2008 Farm Bill defined a food desert as a region where the access to affordable and nourishing food is limited particularly in lower-income communities (110th Congress, 2008). To promote urban sustainability, urban farming practices have resuscitated and garnered increasing interest from public and private entities and policymakers, especially during the era of the COVID-19 pandemic. The C40 Climate Leadership Group consists of a consortium of 97 cities, primarily megacities such as Amsterdam, Beijing, Dakar, Miami, Rio de Janeiro, and Singapore, focused on sustainability with the aim of achieving the Paris Climate Accord goals (C40 Cities, 2020).

Moreover, part of its agenda is to promote urban agriculture targeting food resilience, food self-sufficiency, and local food production according to the 2014 food-related targets, where around 30 % of C40 cities have already set these goals (C40,2014; Davidson & Gleeson, 2015). For instance, large urban farming projects are located in (a) Bangkok, Thailand (22,000 m^2), which utilizes green roofs and landscape architecture to mimic rice terraces (Holmes, 2020); (b) Paris, France (4000 m^2), which employs rooftop farming technologies such as vertical farming (Ball, 2020); (c) The Hague, the Netherlands (0.30 acres or 1200 m^2), which encompasses greenhouses and tilapia farms (Chow, 2016); and (d) Shanghai, China (2.47 acres), which promotes vertical farming activities (Sasaki, 2021).

In the United States, urban farming programs exist in various states, such as California, Florida, Louisiana, New York, South Carolina, Texas, and Washington. Notably, the largest urban farms in the United States are situated in Albuquerque, New Mexico (40 acres); Seattle, Washington (8 acres); Baltimore, Maryland (8 acres); and Detroit, Michigan (7 acres) (Popovitch, 2017). Nationally, Urban Farm Bureaus have been instated in major urban regions to form a coalition to encourage urban farming practices. In the context of sustainable cities, urban and *peri*-urban agriculture contribute to social, economic, and environmental sustainability in congruence with urban resilience. Because the economy is always interwoven with social and environmental sustainability, the environment is the largest factor influenced by economic development and, in turn, affects social sustainability. This can be evidenced by environmental decisions being made contemplating the impact of economic efficiency, equity, and ecosystem conservation (Adger et al., 2003).

As mentioned by Hodson and Marvin (2009), urban ecological security is overlooked because governance is mainly centered in economic development and fails to focus on ecological aspects, including smart growth and sustainable development (Davidson & Gleeson, 2015). The World Bank (1992) defined governance as the “manner in which power is exercised in the management of a country’s economic and social resources for development” (Bank, 1992). Hence, the implemented governance structure should guide the decision-making arena toward sustainable development. In such a sense, policy making should promote social equity and minimize the unexpected externality effect (e.g., market failure) in economics which, in turn, helps achieve economic and environmental sustainability.

Moreover, the role and implications of sustainable indicators and governance have yet to be fully understood (Holman, 2009) with regards to how governance shapes the use and development of indicators (Astleithner et al., 2004). Understanding the circumstances of the development and utilization of indicators can be crucial to guiding governance for sustainability (Moreno-Pires & Fidélis, 2012). Despite the current SDGs already providing insight into global governance, the recognition of the challenges and conditions that led to establishing these goals requires considering existing institutional and policy arrangements (Biermann et al., 2017).

The main goal of this paper is to assess if the current urban agriculture network (UAN) in a metropolitan region can meet the sustainability criteria delineated over the social, environmental, and economic dimensions and understand how to improve network governance, prioritizing the various social, environmental, and economic concerns of urban agricultural sites (UASs). In this paper, we use the clustering analysis to decide how the selected UASs in the study region of a UAN can be implemented in different stages with strategies according to their vulnerability and risk level. Likewise, the scaling up of UASs should follow some sustainability patterns that can maximize the overall sustainability of the UAN. In this UAN, the interacting entities also form organizational networks that have governance structures and functions with an emphasis on three pillars of urban sustainability.

We explore the following questions: (a) Can an integrated clustering and multicriteria decision analysis for pattern recognition in a UAN help gain better social and environmental sustainability while confirming economic sustainability? and (b) Can this managerial strategy of UANs be implemented through an existing or a future governance structure and policy instruments? This paper is organized as follows. First, we introduce the governance structure in the food, energy, and water sectors and identify the sustainability indices used for the evaluation of clustering analysis to help describe the environmental, social, and economic aspects in an UAN. Second, we review the incentive programs available for the food, energy, and water sectors. Finally, we consider the prioritization of UAS clusters, which is expected to resonate with the final stage of UAN growth by a more sustainable way to promote the UN’s SDGs.

2. Methodology

2.1. Study site

The area of interest encompasses the greater Miami metropolitan region, consisting of three of the most urbanized counties in the state: West Palm Beach, Broward, and Miami-Dade. This is also the region that is at ground zero of climate change in the United States, with prominent threats that include sea level rise, hurricanes, and flooding. The UAN of interest in this study is comprised of 23 identified UASs distributed across these counties, which have primarily been demarcated as food deserts by the USDA (see Fig. 1). Geographical information pertaining to each UAS can be found in Supplementary Information Table S1.

In this study, a final benchmark comparison via a ratio method in terms of individual or county-wide food consumption index (FCI), water footprint (WF), and carbon footprint (CF) baseline was organized by two comparative approaches. One approach is the comparison between the selected target UAS and other UASs on an individual basis from which the individual ratio between the individual FCI, WF, and CF and global average in the UAN was generated for comparison in due purpose. The other approach is to carry out the group-wise comparison by calculating the baseline of county average values of FCI, WF, and CF baseline separately from which the individual ratio between the individual FCI, WF, and CF and county average was generated for comparison in due purpose. A base case of three preselected UASs (e.g., sites 2, 10, and 19) within the UAN was arranged for performance comparison in terms of their sustainability indicators throughout the two approaches. These three UASs were selected from three counties (i.e., West Palm Beach, Broward, and Miami-Dade). Each UAS corresponds to one county where they were selected because they have similar agriculture areas ranging between 520–640 m^2 (5000–6900 ft^2). Apart from the consideration of the agriculture land available for crop production, no other parameters were considered to make the characteristics of the base case, which makes the comparison easier.

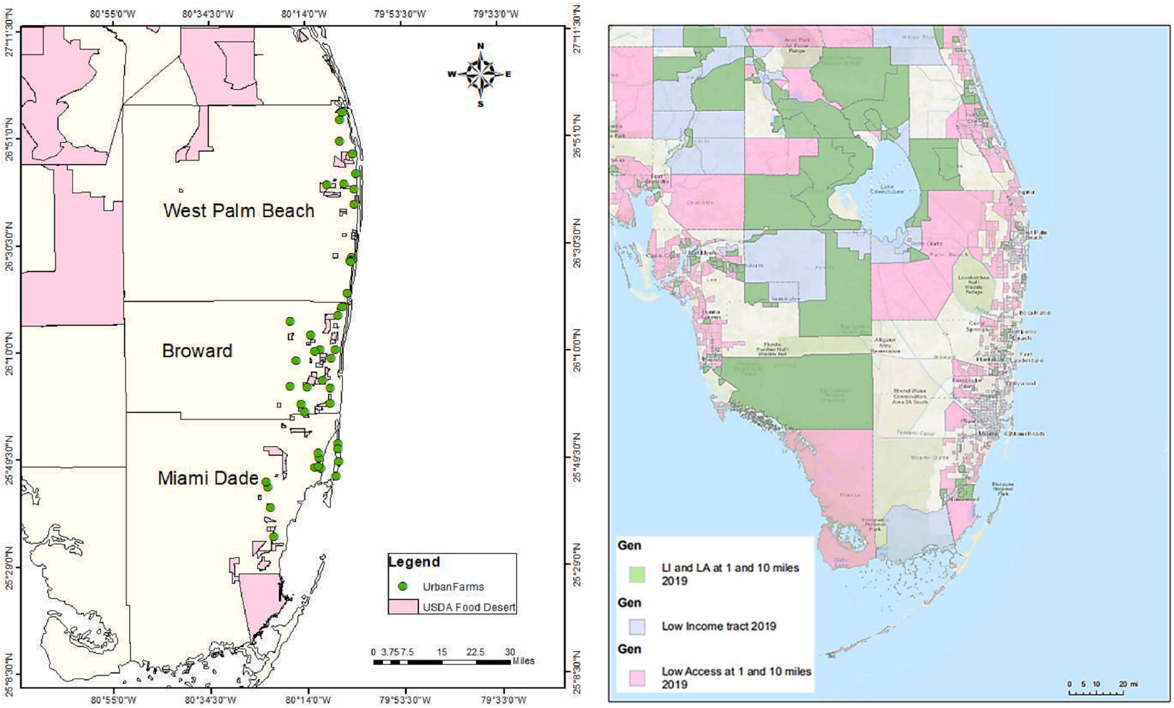
For the most part, these UASs consist of community gardens, apiaries, indoor vertical hydroponic farms, and regenerative agricultural facilities aimed at providing sustainable, clean, and healthy food while engaging the community managed by the city supporting different social functions. The UASs in this area, such as the Urban Farming Institute and Dania Beach Patch, are nonprofit organizations that provide actionable programs, like city-sponsored community gardens, urban farm education, and farmers' markets (Urban Farming Institute, 2022), whereas Harpke Family Farm provides local food to restaurants and hotels based on chef partnerships (Harpke Family Farm, 2022).

2.2. Governance structure and policy context

Moving away from traditional governance is a topic of interest that encompasses neoliberal urbanism and neoliberal governance where policy making involves minimal government interference and limited governance concentrating on market-oriented policies and self-regulating markets (Ives, 2015). Besides, local UASs like the New York City's park, the High Line, as an example of sustainable urban development and community economic growth (Lang & Rothenberg (2017). The governance structure in Miami can be somewhat favorable in providing avenues to individuals participating in urban agriculture at their residence and community, such as in the case of urban farming market (Fig. 2). However, some of these urban agriculture activities have been regulated by the Florida Cottage Food Laws, which manage produce marketing by stipulating the specific items allowed for sale in a residence with annual gross sales below $50,000 and defining approved produce (Division of Food Safety, 2021).

Further, there are also other food policies in place at different governance levels that could affect UASs. For example, fresh-cut produce from UASs can only be sold with permitting, processing, and handling for food safety at locations such as farmers' markets, and food can only be sold within Florida (Florida Department of Agriculture and Consumer Services, 2020).

In addition, other federal food policies regarding food safety are regulated by the U.S. Food and Drug Administration (FDA) and USDA, whereas agricultural land and practices are regulated by the Environmental Protection Agency and Department of the Interior. These agencies establish regulations for low-impact development, stormwater reuse, wastewater reclamation, biosolid applications, and residential zoning and rezoning and help curtail environmental concerns. These concerns include but are not limited to urban agriculture associated with reclaimed water irrigation and landfill compost utilization and could affect food safety and public health. Yet government funding and political support are crucial for effective urban planning strategies, such as carbon market operation or low carbon economy. A further expansion is



(a) (b)

Fig. 1. Visualization of (a) urban agriculture sites and (b) low income and low food access (USDA, 2021) in greater Miami region (Miami-Dade, Broward, and Palm Beach Counties; details of location and cultivation area in Table S1).

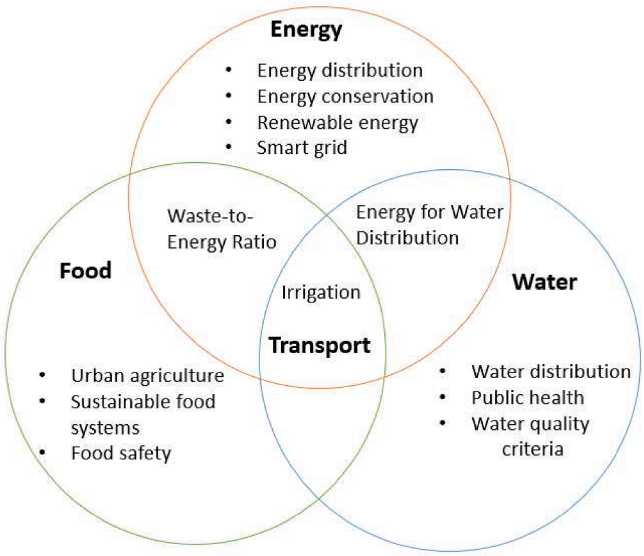


Fig. 2. Implication of governance complexity and policy in food, energy, and water sectors.

the application of incentives and subsidies pertaining to renewable energy generation and UANs help promote certain renewable energy technologies and specific agriculture crops, respectively.

The upscaling of UANs refers to the strategy for prioritization the gradual addition of UASs. Yet this growth strategy is influenced by governance structure and policy instruments. Because the interaction and relationship between stakeholders can be described as networks, network governance structure and function come into play in the context of governance structure and policy instruments. Network management is crucial to evaluate the structure of network governance to meet network change (Fuller et al., 2015; Popp et al., 2013). Network governance structures are employed to tackle challenges via multilateral coordination and involve the management and coordination of resources, information, and activities of at least three organizations (Provan & Kenis, 2008; Rondelez, 2018).

The modes of network governance include self-governed network, lead organization network, and network administrative organization (NAO) (Provan & Kenis, 2008). Self-governed networks are characterized by the distribution of leadership and decision-making among its members. Lead organization networks are a more centralized structure that involve one major member with leadership to manage the network, whereas the leadership in NAOs are located outside of the network. With long-term evolution, network governance structures can become a hybrid of these three modes. Additionally, polycentric governance can be established where multiple organizations partake in the decision-making arena, producing a mixed governance system with multiple governing agents who have distributed leadership, which promotes the potential of group decision-making in an urban food–energy–water nexus. This would involve an urban food production and distribution network, a water governance structure, and an energy distribution network (Fig. 3).

2.2.1. Governance of urban food production and distribution

A centralized food supply system takes care of the connection between multisource food supply systems (food security and nutrition) and urban system as food security policies are driven by top-down and territorial approaches that can be fragmented and lack coordination (Économiques et al., 2016). Further, multilevel food system architecture is affected by territorial governance at different scales that can be also context specific. Nevertheless, this implies that a one-size-fits-all approach is not representative of most of the urban areas. A decentralized governance structure that promotes urban agriculture according to consumer demand, localized sourcing, distribution, and procurement is preferred for sustainable urban development. As the Fig. 3 implies, transitioning toward securing a food supply for food sustainability is central to the interrelated governance structure across food, energy, and energy sectors. Its decentralized decision support is reflected by a self-managed or self-governed network (Fig. 3) where a shared responsibility between different partners is desired. For example, low impact development for stormwater management might affect urban agriculture as the recovery and reuse of stormwater runoff for irrigation is central to the success of the emerging urban agriculture.

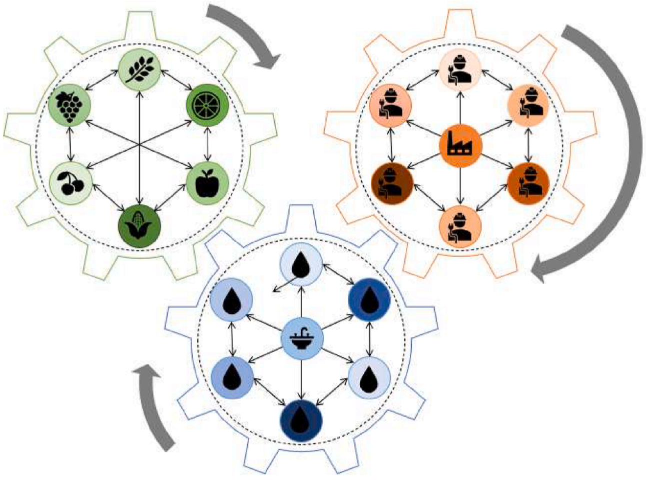


Fig. 3. Network structures and functions in an urban food–energy–water nexus.

However, the current governance structure related to food supply is more closely described by a structure of NAO, where decisions and policy regarding food safety permitting, processing, and handling is primarily controlled by an entity outside of the network (e.g., the FDA and USDA). Because of federal food safety policies and regulations, it can be difficult for UANs to transition to a self-governance and large-scale mode given the advantage of the UAN is to enable the provision of local food sources in dealing with the regular food supply and emergency responses such as COVID-19 or hurricane landfalls in coastal regions.

2.2.2. Food safety and regulations for small food supply operations

There are three different types of food-related businesses: cottage food (i.e., home food processing), commercial food processing facility (e.g., retail and wholesale), and (*peri-*)urban farms in the context of urban agriculture. Specific pertinent food safety regulations can be dependent upon the type of business or operation and the nature of food or produce and regulations or acts in concert with different governance levels (e.g., federal, state). First, at the federal level, the Food Safety Modernization Action of 2011 is the most sweeping reform of the U.S. Food Safety Law since 1938, and it is the most comprehensive regulation applicable to farm produce including urban agriculture.

It also has other relevant regulations, such as preventative controls for human and animal food and sanitary transport rule. For example, for preventative controls for human food, there are specific safety regulations on sanitary operations, equipment and utensils, and personnel. The ongoing hazard analysis critical control points (HACCP) is another federal-level systematic and preventative system, where food safety is addressed through the analysis and control of biological, chemical, and physical hazards from raw material production, procurement, and handling to the manufacturing, distribution, and consumption of the finished product. It breaks down to different types of food, such as juice HACCP and seafood HACCP. At the state level (that is Florida), the Department of Business and Professional Regulations is the regulatory agency responsible for licensing and regulating businesses and professionals, including food trucks, restaurants, farmers' markets, and caterers.

Another important agency is the Florida Department of Agriculture and Consumer Services, which enforces federal regulations on UAS operations without interstate commerce and some retailers. The Florida Cottage Food Law is another important regulation that is especially relevant to urban agriculture. In Florida, based on the Cottage Food Law, individuals can use unlicensed home kitchens to produce for sale of certain foods that present a low risk of foodborne illness (e.g., honey, jams, homemade pasta, etc.). It requires that the selling of Florida-produced cottage foods be restricted to within Florida and not across state boundaries and that they need to be properly packaged and labeled. It also needs to comply with all applicable county and municipal laws and ordinances regulating the preparation, processing, storage, and sale of cottage food products.

2.2.3. *Governance of sustainable water management*

Water governance focuses on water utilization and management, such as allocation, distribution, and equitable use, through establishing legislation and water policy. Here, we refer to water governance as the governance of water stakeholders in decision-making in the UAN context, although the case study is at a local scale and the entities involved in water governance encompass various organizations (i.e., regulatory authorities, community organizations) and individuals. Given the source of surface water or groundwater in a region, the water supply system is mostly a centralized institutional system where decision-making is distributed among the players of the municipal authority (Fig. 3). Managerial policies are enacted by local, state, and federal legislation via centralized governance.

Policy instruments can also affect the supply chain of water for urban agriculture irrigation. With the current operations in South Florida, most urban growers use groundwater for irrigation, which is a free resource except for the initial cost for pump installations. Few operations use tap water or city water due to the high cost, and such practices are more applicable to productions systems like aerophonics or hydroponics, which have higher standards of water quality and water chemistry but also possess high water use efficiency. Using reclaimed water (e.g., rainwater, stormwater, wastewater) can have great potential toward sustainable practices. However, this is not widely adopted in South Florida, due to the lack of infrastructure for sizable operations in urban food production. We observed that some urban growers use rain barrels connecting to rooftops to supplement water needs for irrigation as well as water from small urban ponds.

Yet the combination of stormwater reuse provides an additional layer to decrease community vulnerability to water shortages, especially with concerns of climate change and substantial drawdown of the groundwater table. Stormwater reuse, with other low-impact development strategies, can support urban agriculture irrigation and be further linked to combating climate change because stormwater can be utilized as an alternative water supply to support urban agriculture in drought events. In this context, the governance structure is a hybrid centralized and decentralized system (Fig. 3) that can be more reliable to the UAN because decentralized systems can have pros and cons relative to centralized systems (Goldthau, 2014).

2.2.4. *Governance of energy production and distribution*

Based on the characteristics of the energy sector, which has fewer restrictions and regulations in comparison to the food and water sectors that are sensitive to health and welfare, it can be easier to manage policy wisely. Unlike food and water that go directly to the consumer or the production process, energy is more of a service and is intangible by comparison. Energy governance encompasses energy service and supply distribution; however the governance structure is fragmented (Escribano, 2015), with the polycentric structure better reflecting the governance structure in energy sector (Goldthau, 2014). Based on the networked characteristics in an urban food–energy–water nexus, it seems a lead organization governance structure can be selected (Fig. 3) because it is a more centralized structure that involves one major member (energy-generating facility) to manage the network of power distribution.

The electricity generated by a centralized facility is distributed through the electric power grid to multiple end users like the UASs. However, with the potential inclusion of a local microgrid, energy storage units, and renewable energy production technologies that can operate as decentralized energy sources, the UAN can have a hybrid energy supply system between the centralized and decentralized operation modes. Further, there are also governance structures to promote sustainability and energy security. This type of decentralized energy source can not only provide a better energy reliability to the UAN but also decreases the carbon footprint (CF) associated with energy from fossil fuels, hence enabling the UASs to transition to be more sustainable for UANs to meet SDGs in the future.

2.3. *Sustainability indices*

The EU SDG indicator set was first presented in 2017 by the European Commission addressing progress toward the 17 SDGs and was revised in a 2021 report to consider EU policy and monitor the progress toward meeting the SDGs (European Commission, 2020). Moreover, sustainable indices also aid in the quantification of sustainable urban development (Verma & Raghubanshi, 2018). Trade-offs among social, environmental, and economic sectors are expected with respect to those selected sustainability indices that vary over the sustainable development options (Mori & Christodoulou, 2012b).

Yet the emphasis of sustainable development differs according to the interpretation of those sustainability indices (Tanguay et al., 2010). Therefore, transitions toward urban sustainability via multiple sectors presents a pathway instead of providing a direct evolution (Pupphachai & Zuidema, 2017). A quantification of progress toward sustainable development with respect to various sustainability targets can be achieved by delineating sustainability indices to support decision-making with linkage to urban governance structures and functions (Mayer, 2008; Pupphachai & Zuidema, 2017).

The selection of sustainability indices are dependent on the objectives or interest for sustainable development and can be extremely broad, such as the measurement of CO_2 emissions (Pupphachai & Zuidema, 2017), natural capital index, ecological footprint index, and welfare index (Mori & Christodoulou, 2012b). For instance, it is beneficial to use local sustainability indicators to address local governance and policy among the pool of 29 local indicators presented by Tanguay et al. (2010). These include crime rate, daily water consumption per person, unemployment rate, GHG emissions, and population density.

Because there are various aspects of sustainability, sustainability performance can be measured via sustainability indices in a similar approach that encompasses environmental, social, and economic indicators tied to legal aspects. These indices also help explore and connect urbanization and urban agricultural practices as summarized in Table 1. For example, carbon footprints can be linked to policy instruments aimed for carbon neutrality and GHG emission reduction. Conversely, water footprints can be associated with water conservation and climate change effects. The food consumption index can link population, local food production, and food security. For environmental sustainability, indices related to environmental impact, such as CF (kg CO_2-eq), WF (L), and sea level rise (m), are considered.

In social sustainability, indices related to population density, food availability, and social equity, such as the FCI, unemployment index (UI), and crime rate index (CRI), can be evaluated. In the economic sector, crop production index (CPI) is used to explore the economic sustainability with respect to income generated by crop produced at local scale, and water reuse potential (WRP) relates the reduction of reclaimed water demand for irrigation by stormwater per agriculture

Table 1
Summary of sustainability indices applied in this study.

Sustainability	Index	Description
Environmental aspects	Carbon footprint	Carbon footprint resulting from GHG emissions related to crop harvesting and local crop production
	Water footprint	Water footprint resulting from water consumption related to local crop production
	Sea level rise	Climate change impact prediction of sea level rise according to NASA-IPCC AR6 scenario SSP5-8.5 (low confidence) projections
Social aspects	Food consumption index	Relation between food consumption and approximate population density near the urban farms
	Unemployment index	Standard values for the unemployment rate
	Crime rate index	Standard values for crime rate
Economic aspects	Crop production index	Used to calculate the income generated from the crops produced in each urban farm utilizing Florida price (pf) and national crop price ($pf_{nat.}$)
	Water reuse potential	Cost of water reuse potential is a ratio comparing the cost of reclaimed water supply for irrigation after utilizing an alternative water supply (e.g., stormwater) per UAS area (Assuming stormwater storage of 20,000 $L \cdot yr^{-1}$)

Table 2
Carbon footprint and water footprint based on crop production for UASs.

UAS	Number of crops	Carbon footprint ($kg\ CO_{2\text{-}eq} \cdot yr^{-1}$)	Water Footprint ($L \cdot yr^{-1}$)
1	4	1.76×10^3	0.229×10^6
2	3	0.532×10^3	0.326×10^6
3	5	1.17×10^3	0.926×10^6
4	7	5.44×10^3	2.27×10^6
5	9	10.6×10^3	2.68×10^6
6	13	8.96×10^3	1.03×10^6
7	7	1.57×10^3	0.345×10^6
8	3	4.37×10^3	0.445×10^6
9	12	1.60×10^3	0.443×10^6
10	4	2.83×10^3	0.380×10^6
11	11	3.52×10^3	0.966×10^6
12	7	5.34×10^3	1.60×10^6
13	7	4.16×10^3	2.26×10^6
14	5	17.6×10^3	3.13×10^6
15	4	5.40×10^3	4.61×10^6
16	7	31.4×10^3	8.61×10^6
17	2	0.287×10^3	0.136×10^6
18	4	0.357×10^3	0.296×10^6
19	12	2.28×10^3	0.633×10^6
20	12	2.72×10^3	0.703×10^6
21	9	5.63×10^3	1.39×10^6
22	11	6.29×10^3	1.73×10^6
23	12	1.76×10^3	0.229×10^6

site area. Accordingly, the sustainability will be assessed for the 23 UASs selected in the UAN of interest as well as cross-comparison corresponding to the grouped UASs by their inherent characteristics.

2.3.1. Environmental sustainability

The analysis on environmental sustainability focuses on the analysis of water footprints and carbon footprints from the production and consumption of resources in the UASs and their activities of related people and entities. The carbon footprint related to the GHG emissions is associated with production activities in the UAS described in Eq. (1). Similarly, the water footprint quantity of water consumption from crop production activities is described in Eq. (2).

$$CF = area_{crop} * yield_{crop} * GHGEF_{area\ of\ crop} \tag{1}$$

$$WF = area_{crop} * yield_{crop} * WCF_{area\ of\ crop} \tag{2}$$

where CF is the crop carbon footprint and contribution of GHG (i.e., carbon dioxide) emissions (kg $CO_{2\text{-}eq}$), $area_{crop}$ is the area for crop production (m^2), $yield_{crop}$ is the maximum annual crop yield ($kg \cdot m^{-2}$), and $GHGEF_{areaofcrop}$ is the GHG emissions factor for each crop (kg $CO_{2\text{-}eq} \cdot kg^{-1}$). Likewise, WF is the total water footprint and water consumption (L), and $WCF_{areaofcrop}$ is the water consumption factor for each crop (kg $CO_2 \cdot kg^{-1}$).

Additionally, the analysis of sea level rise was performed according to the projections acquired from the IPCC AR6 report according to NASA-IPCC AR6 scenario SSP5-8.5 (low confidence) that accounts for possible climate change to having extremely high GHG and CO_2 emissions from climate change impact (Masson-Delmotte et al., 2021), with the projection for total sea level rise of 0.15 m by 2030 obtained from NASA's sea-level projection tool utilizing the IPCC AR6 report (NASA, 2022).

2.3.2. Social sustainability

Social sustainability indices can include information like supply chain, location, social innovations, training and education, health and safety, and so on (Husgafvel et al., 2015). Social sustainability is the relation between stakeholders and social development. Further, quality of life, governance, diversity, equality, food security, and social equity are other indices analyzed in describing sustainable development (Dempsey et al., 2011; Talan et al., 2020). In this case, we examined specific aspects of social sustainability, such as the unemployment rate, the crime rate, and food security in the context of food availability. Crime rate and low income affect UASs and, therefore, can help determine which urban farming location needs to receive priority support, leading to a decreased crime rate via urban agriculture activities.

The low access is defined by USDA when at least 33 % of the population or 500 people live more than 1.6 km (1 mile) from a supermarket or grocery store in urban regions. However, to describe food availability via the FCI, we used the average daily dietary food uptake for an adult of 4 kg (World Health Organization, 2003) to determine the food demand according to the relationship between food consumption and approximate population density near UASs. The population near the UASs was determined based on the area of local UAS community and the population density ($cap \cdot km^{-2}$) obtained from the postal zip code corresponding to each farm (U.S. Zip Codes, 2022). Considering 33 % of the population in low-access regions surround the UASs, the theoretical population near each UAS is obtained by considering the population density that can be sustained by the agricultural area and factoring for the 33 % of the population being fed by each UAS. Thus, the FCI is obtained from the ratio between the average daily food consumption (fc_{UFA_i}) and food production (fp_{UFA_i}) as described in Eq.3. If FCI > 1, it represents a greater food demand over food supply.

$$FCI = \frac{fc_{UFA_i}}{fp_{UFA_i}} \tag{3}$$

The UI and CRI were collected from the U.S. Census Bureau from the 2019 American Community Survey 5-year estimate (U.S. Census Bureau, 2022) and the interactive crime map using data from a private data provider, ATTOM Data Solutions (ADT, 2019).

2.3.3. Economic sustainability

Economic sustainability can integrate the elements that stimulate economic growth in sectors such as food, energy, and water. These should be capable of supporting a given system (e.g., community or population). For example, cost analysis for local food production and food consumption in relation to energy supply via a utility grid and/or microgrid can provide an idea of economic sustainability. Similarly, comparison of reclaimed water and stormwater consumption and cost of water utilization can further provide insight into economic sustainability.

The CPI index is used to calculate the income generated from the crops produced in each UAS (fp_{UAS_i}) utilizing Florida price (pf) and national crop price ($pf_{nat.}$), which are obtained from the USDA (Table S2). For simplicity in comparing UASs, 15 crops (i.e., snap bean, cabbage, corn, cucumber, pepper, tomato, eggplant, squash, potato, lettuce, spinach, onion, okra, and radish) generally produced by the UASs are presumed to be cultivated throughout the agricultural sites, although not all are cultivated through the 23 UASs (Table S3). Assuming that equal quantities of each crop are cultivated at each farm (based on area), the estimated income can be derived based on the Florida fresh market price (Eq. (4)).

$$CPI = \sum_{i=23} fp_{UAS_i} * pf \tag{4}$$

The WRP index is a ratio comparing the cost savings from using an alternative water supply (e.g., stormwater) and the cost of the reclaimed water supply per UAS area (Eq. (5)).

$$WRP = \frac{(WS - SWS) * RW_{cost}}{UA_{area}} \tag{5}$$

where WS is the water supply ($m^3 \cdot yr^{-1}$), SWS is the stormwater supply ($m^3 \cdot yr^{-1}$), RW_{cost} is the cost of reclaimed water supply ($\$ \cdot m^{-3}$), and UA_{area} is the area of an UAS (m^3).

2.4. Spatial analysis of UAN from optimal governance perspective

2.4.1. Urban farm clustering

Many urban spatial patterns have been evolving into being more polycentric than centralized patterns (Wang et al., 2020). Most metropolitan cities can be described as polycentric urban regions characterized as polycentric urban networks (Kloosterman & Lambregts, 2001). While implementing clustering methods, the dissimilarities between the observations assigned to each cluster can form an emerging UAN. Thus, the clustering analysis aims to agglomerate the UASs in a UAN for exploring UAS growth. Within this context, the sustainability assessment of the UASs in the UAN must consider the intersections among social, economic, and environmental sustainability and its implications of being equitable, bearable, and viable (Fig. 4) because all three pillars of sustainability should be addressed to attain a truly sustainable development (Tasdemir et al., 2020). Along with this philosophy, three sectors of food, energy, and water can be better structured with governance and policy for resources distribution for the public at large (Fig. 3).

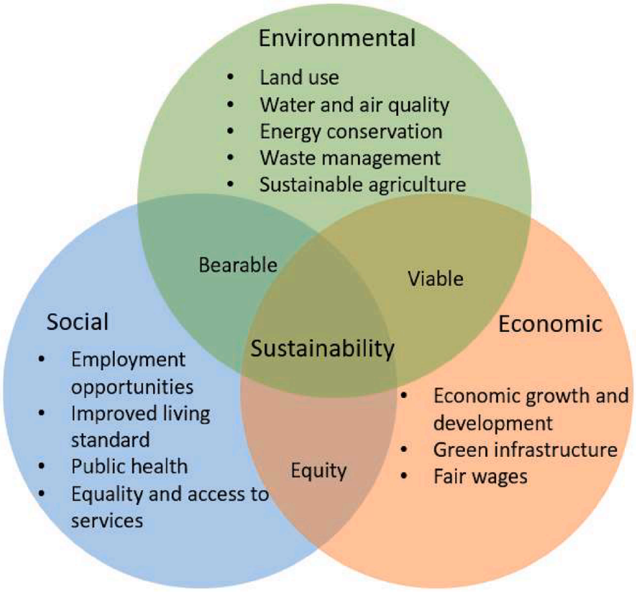


Fig. 4. Summary of the realm of clustering analysis for three pillars of sustainability.

Geo-clustering has been presented in various clustering analyses, including k-means clustering, hierarchical clustering, and density-based spatial clustering. For example, the three-dimensional (3D) feature space iterative clustering method with noise control was applied for image clustering by Guo and Haigh (1994) in a 3D feature space. But Wu et al. (2018) used gray clustering analysis for classifying multiple elements and objects in a system that may have uncertainty and fuzzy factors.

Further, fuzzy classification was used to classify the feature vector of vehicle feature space (Astapov & Riid, 2015) and processing 3D brain magnetic resonance images (Kong et al., 2019). Optimal clustering in high-dimensional spaces has been applied to data that may have a high degree of noise in grid clustering (Hinneburg & Keim, 1999) and high-dimensional clustering of single-cell data of antibody panels (Brummelman et al., 2019). In this study, we employ k-means clustering algorithms to analyze clusters based on high-dimensional data embedded in different UANs, projecting more than 10 indices in a 3D feature space with respect to social, environmental, and economic sustainability patterns. Variation in the number of clusters in k-means clustering analysis helps assess how the UASs can be grouped into varying levels of sustainability.

The k-means clustering algorithm can form grouping based on assigning data points to a centroid (i.e., the centroid is the center point of the object) with respect to Euclidean distance between the centroid and the data point locations. It can be manipulated in an iterative process that averages the points in the cluster and adjusts the centroid to the updated location (Chikumbo & Granville, 2019). In a 3D feature space, the Euclidean distance (d) is determined from point A = (x_1, y_1, z_1) and B = (x_2, y_2, z_2) is described by Eq. (6).

$$d(A,B) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{6}$$

Mathematically, the aim of k-means clustering algorithm is to minimize the sum of squared errors within the Euclidian distance. Further, the k-means clustering algorithm clusters data without given classification categories. In this optimization process (Eq. (8)), the objective function f is to minimize the sum of the squared Euclidean distance of each point to the nearest centroid as specified in Eq. (7), where k represents the specified number j of clusters (j = 6, 8, 10, and 12 in this study), m is number of features for sample data i, X = (x_1, …,x_n) are a set of data points, c = (c_1, …, c_j) represents a cluster set, and c_j is a centroid of cluster j. To implement the k-means clustering algorithm, we explored the number of iterations required for convergence and specified the maximum number of iterations per run as five iterations based on our results.

$$f = min \sum_{j=1}^{k} \sum_{i=1}^{m} \left| \left| x_i - c_j \right| \right|^2 \tag{7}$$

The k-means clustering strategies are formulated with respect to 10 criteria that are implicated in the determination of the priority index (PI): (a) sustainability (social, economic, and environmental), (b) governance (agriculture funding for UASs), and (c) geographical location (proximity to food desert). Each criterion has unique attributes identified as A_1 = CRI, A_2 = UI, A_3 = FCI, A_4 = CPI, A_5 = WRP, A_6 = CF, A_7 = WF, and A_8 = effect of sea level (SL) rise by 2030 according to IPCC AR6 SSP5-0.6. If a UAS is affected by sea level rise, assign a value of 1; otherwise, assign 0. These three strategies echo the three pillars of sustainability (Fig. 4). Attributes identified in governance are A_9 = government funding (PF) for food distribution (if nonprofit or public, assign value of 1, otherwise 0). We noted that most UASs (labeled as community gardens) are nonprofit organizations or are managed by public entities (e.g., town or city). A_{10} = proximity to food desert (FD) (If situated near food desert, assign value of 1, otherwise 0).

However, before implementing the k-means clustering algorithm, scaling and normalizing these attributes is performed where the 10 attributes of the data set were first standardized according to Eq. (8). Here n_{ik} = standardized sustainability index for attribute k of UAS i, X_{ik} = attribute value for sustainability index k, $\overline{X}_{ik}$ is the mean attribute value, and s_i is the standard deviation of i. This was done by using Scikit-learn's StandardScaler package. The standardization is important to avoid possible bias when assigning weights related to the importance of each attribute because the values for the attributes are scattered over different ranges.

$$n_{ik} = \frac{X_{ik} - \overline{X}_i}{s_i} \tag{8}$$

Because proximity plays a vital role in many aspects of an urbanization process, the competitiveness in economic activities are site-specific in some cases (Kloosterman & Lambregts, 2001). The geospatial data of the UASs were thus transformed from latitude and longitude to Cartesian coordinates by applying a 100 × 100 grid matrix that overlays in the ArcGIS map for plotting in a 3D space later in the clustering analysis.

2.4.2. Prioritization of UAS clusters via multicriteria decision-making

To evaluate the implementation of clustering analysis for ultimate prioritization of the UAS clusters, the various intrinsic criteria or attributes can be ranked in order of importance. For example, in multicriteria decision-making (MCDM), the technique for order preference by similarity to the ideal solution (TOPSIS) (Behzadian et al., 2012) can be employed to generate weights for each sustainability index to echo the importance given to the individual cluster condition. Thus, a decision-making problem can be solved after conducting and evaluating the clustering strategies for the specified attributes.

However, this MCDM process can be implicitly implemented directly to the clustering analysis, where the desired weights are assigned to the sustainability indices before the application of the clustering algorithm to assess the alternative scenarios (e.g., values and assumptions) in shaping the outcome of complex decision-making. Hence, to couple all the aspects of sustainability, the sustainability weight index is determined as follows for the sustainability indices for social, environmental, and economic sustainability. Given the different scenarios, the assignment of criteria weights reflects the importance of the criteria in the decision-making (Mateo, 2012).

$$w_{kj} = m_j n_{ki} \tag{9}$$

where w_{kj} = weighted standardized vector for attribute/criteria j for UASs, $i = \{1, \ldots, 23\}$, m_j = assigned importance of criterion {0,1}, and n_{ki} = standardized sustainability index for attribute j of UAS i. A common weighting method is the weighted score (Odu, 2019) based on the order of importance, and hence, the values assigned for the weighting factors range between 0 and 1 because the total score should be 1 or 100 % (Németh et al., 2019).

The first scenario or equal sustainability scenario (S1) gives the same weighting factors to social, economic, and environmental sustainability (i.e., $m_j = 0.1$ for each index). The second scenario or climate prioritization scenario (S2) accentuates the climate change impact (specifically CF, WF, and sea level rise), thus assigning $m_j = 0.2$ to CF, WF, and sea level rise, and $m_j = 0.0571$ to each of the remaining indices. The third scenario, economic prosperity scenario (S3), highlights the economic gain (CPI) from local food production and possible cost savings from the inclusion of stormwater by reducing reclaimed water demand for irrigation (WRP), thus also assigning $m_j = 0.2$ to CPI and WRP and $m_j = 0.075$ to each of the remaining indices.

The decision-making matrix is composed of the summation across the 10 criteria ($j = 1, \ldots, 10$) pertaining to sustainability concern (social, environmental, and economic sustainability indices), optimal governance (agriculture funding support for UASs), and sensible location (proximity to food desert; Eq. (11)). The direction from each attribute considers how precarious each UAS could be as summarized by using the PI. For instance, the UI, CI, FCI, CPI, WRP, CF, WF, sea level rise, PF, and FD would all have a positive direction because it is desirable to commence the upscaling process across UASs that are under more distressed conditions regarding food insecurity, societal crime control problems, and salient environmental impacts.

$$PI = \sum_{k=1}^{n} w_{ij} \tag{10}$$

Last, to decide the priority of promoting these UAS clusters in a UAN, the ranking is performed accoding to the PI value, where the highest PI signifies higher priority in a UAN to promote due to its precarious situation.

Further, the scenarios can be assessed to help stakeholders and decision-makers understand which scenario needs greater attention for the implementation in a UAN. Using summations of the weighted vectors (w_{kj}) determined and normalized for the attribute or criterion derived from each scenario in the MCDM process, the three scenarios can be ranked according to the PI score, in which a PI closer to 1 is preferred (Abidin et al., 2016). First, the weighted vectors are normalized (r_{ij}) (Eq. (11)), and second, the scenario is selected for the highest calculated score P_i (Eq. (14)).

$$r_{ij} = \frac{w_{kj}}{\sqrt{\sum_{j=1}^{n} w_{kj}^2}} \tag{11}$$

$$S_i^+ = \left[\sum_{j=1}^{n} \left(w_{kj} - v_j^+\right)^2\right]^{1/2} \tag{12}$$

$$S_i^- = \left[\sum_{j=1}^{n} \left(w_{kj} - v_j^-\right)^2\right]^{1/2} \tag{13}$$

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{14}$$

where S_i^+ = positive distance between alternative and overall score for alternative i, and S_i^- = negative distance between alternative and overall score for alternative i. Here v_j^+ = ideal best value based on w_{kj}, v_j^- = ideal worst value based on w_{kj}, and P_i = score of alternative i.

3. Results

3.1. Sustainability assessment

We performed the evaluation of sustainability indices to try and undertake the three aspects of sustainability with the social, environmental, and economic dimensions of the UAN as mentioned by Mayer (2008). We used local indicators to evaluate and support local decision-making (Tanguay et al., 2010). The assessment of environmental sustainability provided insight to GHG emissions and water consumption for each UAS as well as possible impact from sea level rise based on projections for 2030 (Fig. 5). With GHG emission factors (kg $CO_{2\text{-eq}}\cdot m^{-2}$) and water consumption factors ($L\cdot kg^{-1}$) for urban agriculture irrigation from the literature (Table S5), we estimated the CF and WF for each UAS. It is noticeable that the estimated values of CF and WF were based on the inventory of dominant crops documented for production at each UAS (Tables S3 and S4); hence, farms that grew more crops tended to have a higher CF and WF (Table 2). For the base case that corresponded to the UAN consisting of three UASs (UAS2, 10, and 19), the UAS with the lowest CF and WF was UAS2, followed closely by UAS10.

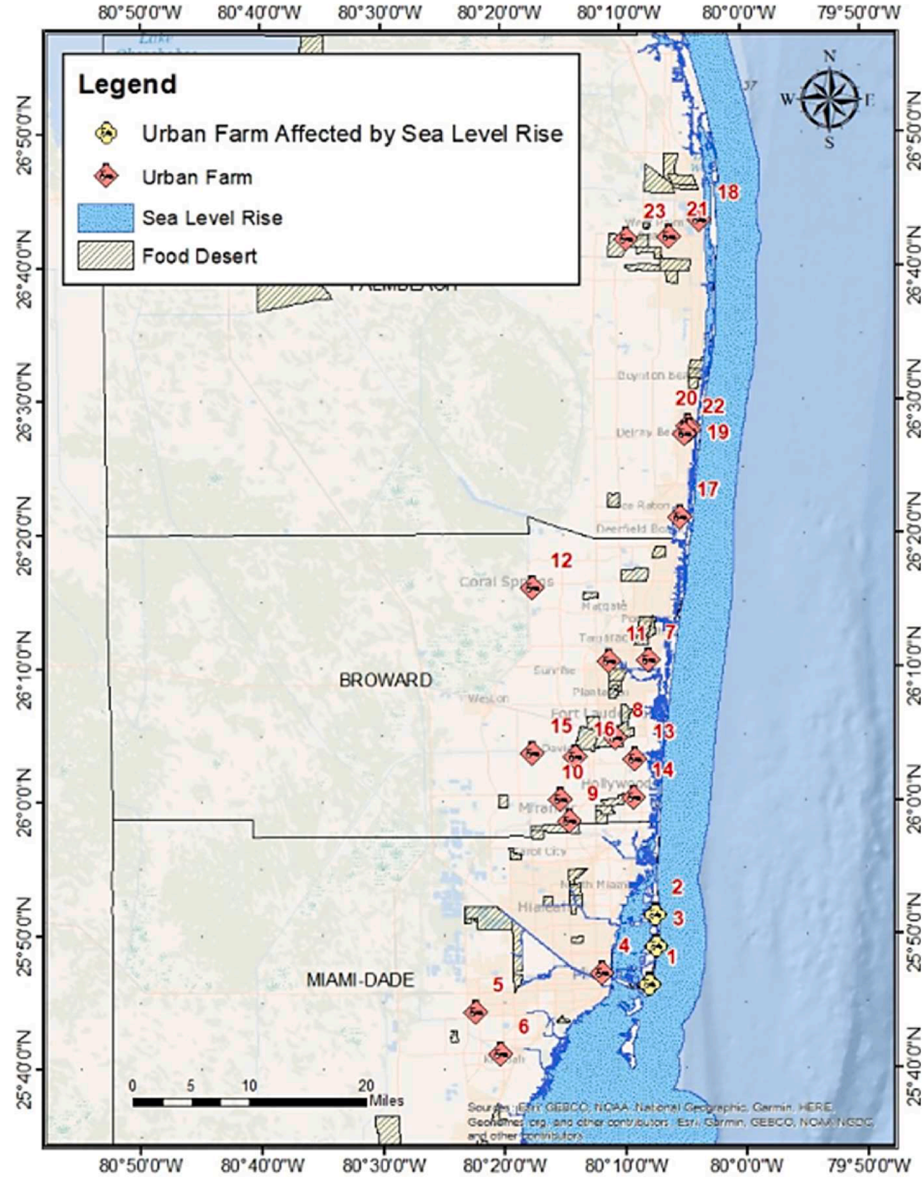


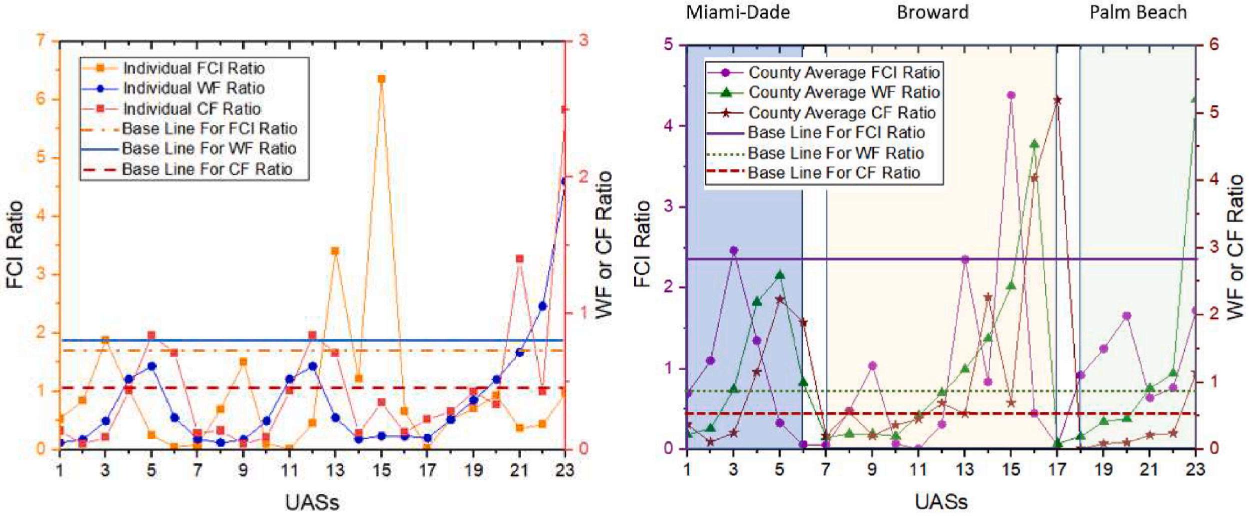
Fig. 5. Location of UASs with respect with sea level rise for 2030 according to NASA-IPCC AR6 scenario SSP5-8.5 (low confidence).

Out of the selected 23 UASs, UAS5, UAS14, and UAS16 obtained the highest carbon and water footprints related to crop production.

After performing the sea level rise projection according to NASA-IPCC AR6 scenario SSP5-8.5 (low confidence), we found that UAS1, UAS2, and UAS3 located in Miami-Dade will be affected with flooding according to a 300-meter delineation range (Fig. 5). Two of these UASs (i.e., UAS2 and UAS3), along with UAS4, UAS9, UAS13-15, UAS20, and UAS23, showed large FCIs, indicating greater food demand in relation to food production. A suggestion to decrease the FCI and provide a larger food supply in this area can be made possible by expanding the current cultivation area of the UASs. However, considering the possible impact of sea level rise in the future at UAS1, UAS2, and UAS3, it may be more feasible to incorporate a new UAS at a location that may not be affected by coastal flooding given the projected sea level rise. This can call forth the need for additional policy instruments, incentives, and subsidy programs to aid in the sustainment of the UASs. Additional options can be evaluated to pinpoint some private and public entities that may develop more UASs with a high sustainability level, such as UAS15. In a sense, having multiple UASs in the UAN provides a form of robustness as to the case of climate change impact assessment.

Other important aspects in regard to social sustainability are the observed large unemployment rate and crime rate at UAS4 relative to other UASs. The unemployment rate is ~ 2.2 times higher than the 2021 national average unemployment rate of 5.3 % (USDL, 2022). However, the crime rate was slightly below the 2020 national crime rate of 387.8 (per 100,000 general population) (Grimes, 2021). For economic sustainability, usually the UASs with a larger agricultural area exhibited a higher CPI, such as UAS14, 15, 16, and 23, related to its production potentials. The possible income from crop production is one important benefit to areas that suffer from economic inequity; hence, this income can stimulate further urban agriculture in the UAN, thereby concurrently increasing its social sustainability. Yet, governance and policy have to be evaluated to determine if rectification is needed to enable the avenue for this transition in the UAN.

Comparison of the sustainability patterns in an UAN can be made possible with respect to food security (e.g., FCI) and environmental impact (e.g., CF and WF) over each individual UAS or each group of UASs in each county. Fig. 6a shows the performance comparison of the individual UAS relative to the global averages of all UASs in the UAN. The three selected target sites of UAS2, 10, and 19 may be highlighted



(a)

(b)

Fig. 6. Comparison between (a) FCI, WF, CF ratios for individual UAS relative to global baseline in the UAN (b) FCI, WF, and CF ratios for individual UAS relative to each county average as shown by different shaded area and global county averages in the UAN.

for demonstration. In this context, UAS2 with a FCI ratio of 0.839 is 16.1 % lower in comparison with the global average of the FCI ratio in the UAN, implying that there is greater food demand than food production at UAS2. As for UAS10 and UAS19, the same ratio was 0.105 and 0.704, respectively, indicating the FCI ratio was 89.5 % lower for UAS10 and 29.6 % lower for UAS19 in comparison to the global average of the FCI ratio in the UAN. However, the individual CF ratio was 0.042, 0.225, and 0.181 for UAS2, 10, and 19, respectively indicating that the CFs for the three preselected UASs as base case were lower than the global average of CF ratio in the UAN, while being 95.8 % lower for UAS2, 77.5 % lower for UAS10, and 81.9 % lower for UAS19. Moreover, UAS2 with a WF ratio of 0.174 had a value of 82.6 % lower WF than the global average of the UAN. UAS10 and UAS19 had a WF ratio of 0.203 and 0.338, respectively. Finding in this case displayed 79.7 % and 66.2 % lower WF ratio than the global average of WF ratio in the UAN, respectively. The performance comparison between other UAS relative to the base case can be further evaluated by the same way using the global averages (i.e., horizontal base lines) In Fig. 6(a).

When considering the benchmark comparison based on the county averages as shown in Fig. 6(b), the three preselected target sites (e.g., UAS2, 10, and 19) may be chosen again for demonstration to signify the implication of scaling up the UAN from a regional perspective. Regarding the base case for the FCI ratio in Fig. 6(b), UAS2 had a ratio of 1.10 suggesting that the individual FCI ratio is 10 % higher than the county average of FCI ratio of the UASs in Miami-Dade County. Besides, UAS10 and UAS19 had a FCI ratio of 0.07 in Broward County and 1.25 in Palm Beach Counties, respectively, indicating that the individual FCI ratio obtained for UAS10 was 93 % lower while for UAS19 was 25 % higher than the county average of the FCI ratio. When comparing with regards to CF and WF ratios, UAS2 obtained a ratio of 0.11 and 0.26 indicating an 89 % and 74 % lower carbon and water footprints relative to the county average of the CF and WF ratio, respectively. UAS19 had a ratio of 0.09 for CF and 0.34 for WF relative to the county averages of the CF and WF ratio. It is indicative that the CF and WF ratio for this UAS is approximately 91 % and 66 % lower than the county average of the CF and WF ratio, respectively. Similarly, the comparison in terms of the performance of other UASs relative to the global averages can be visualized by using the horizontal base lines for the global averages of FCI, WF, and CF ratios as shown in Fig. 6(b). When comparing the global results of the UAN with the three preselected target sites in the base case, the results support the network expansion with the inclusion of more UASs. This is evidenced by that two of these three UASs in the base case did not have favorable results. We predicted that UAS2 will be affected by sea level rise and flooding, while UAS2 and 19 had similar FCI ratios representative of greater food demand than food supply and UAS2 and 10 had close values of unemployment rate.

3.2. Clustering analysis of the urban agriculture sites

The clustering analysis leads to generating the PI, which aggregates all the predefined indices. The individual visualization of the social, environmental, and economic sustainability for each cluster can then help clarify the overall level of sustainability in a UAN (Fig. 7). For instance, UAS15 has greater food demand, as demarcated by the larger FCI, and the highest crime rate is at UAS4 (Fig. 7a). Although UAS1, UAS2, and UAS3 are affected by sea level rise, UAS17 has the highest CF and and UAS16 the highest WF among all the UASs (Fig. 7b). The UASs in proximity to food deserts includes UAS1, UAS2, UAS3, and UAS12 (Fig. 7c). It is noticeable that most UASs are supported by government funding with four exceptions, including UAS8, UAS15-16 and UAS23.

The analysis of the UAN can follow those clusters that maximize the sum of the different sustainability levels of the 23 UASs (Fig. 8), which can be easily summarized by PI across three scenarios (Table 3). The three proposed scenarios in this study try to address the impact of varying aspects of sustainability for each UAS. The equal sustainability scenario (S1) provides a base for comparison, with similar importance placed in all the criteria for decision-making, whereas the climate prioritization scenario (S2) and economic prosperity scenario (S3) prioritize climate change impact and economic gain (CPI) from local food production, respectively. Visual comparison of both S1 and S2 yielded a similar relationship for all k-clusters (6, 8, 10, 12) except for S3 according to the 3D feature space (Fig. 8).

To further showcase the clustering results, we selected the case of k = 8 clusters for further assessment and visualization of the three scenarios because this clustering scheme in general has a distribution of at least two UASs per cluster (Fig. 9). To accommodate sustainable urbanization, polycentric evolution in expansion and growth may be more appropriate for the UAN because polycentric urban development considers the shift of urban clusters followed by the reshaping of regions from population growth. The formation of subcenters has resulted in a polycentric spatial pattern exhibited in the urban regions driven by urban spatial dynamics (Broitman & Czamanski, 2015). For instance,

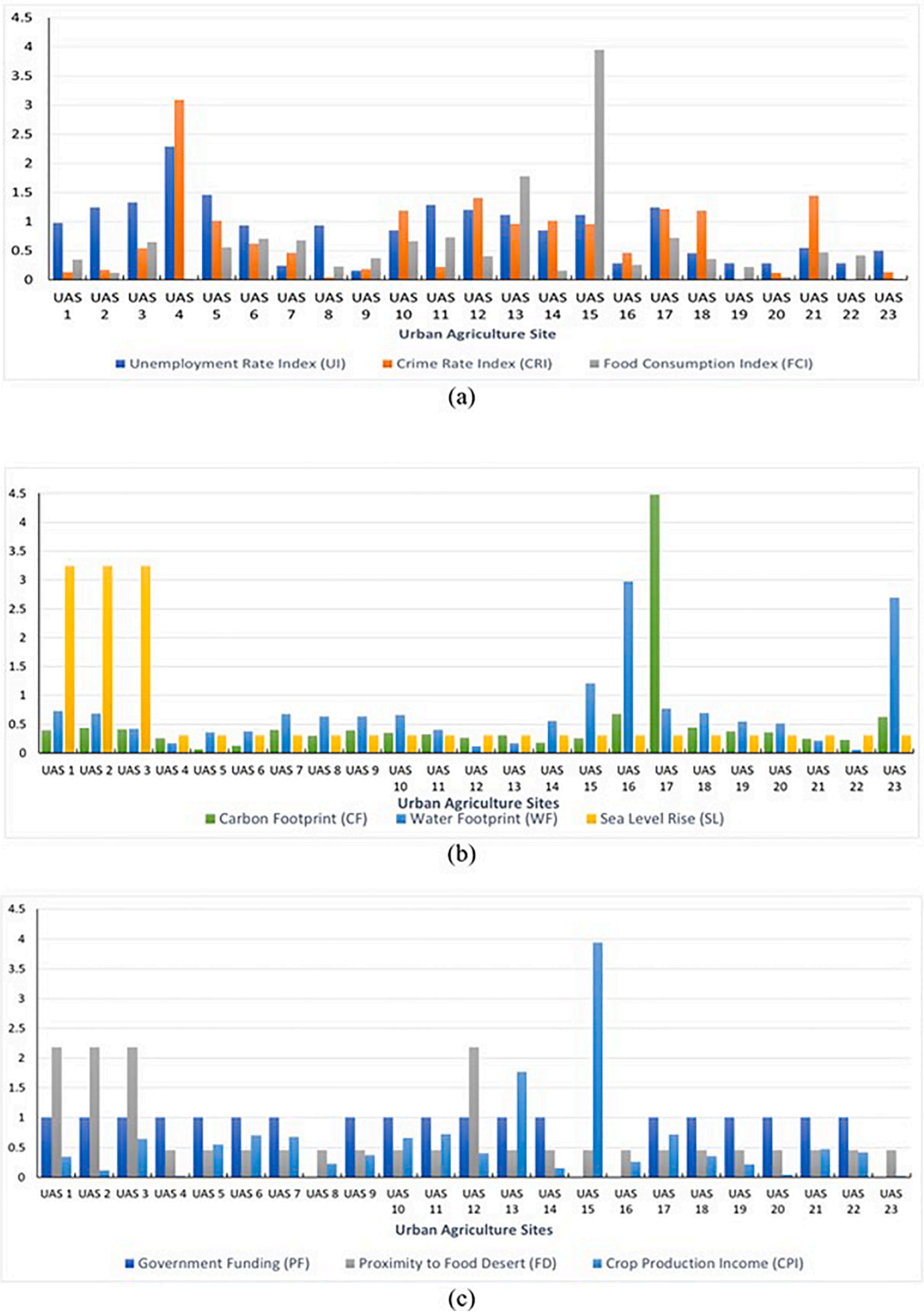
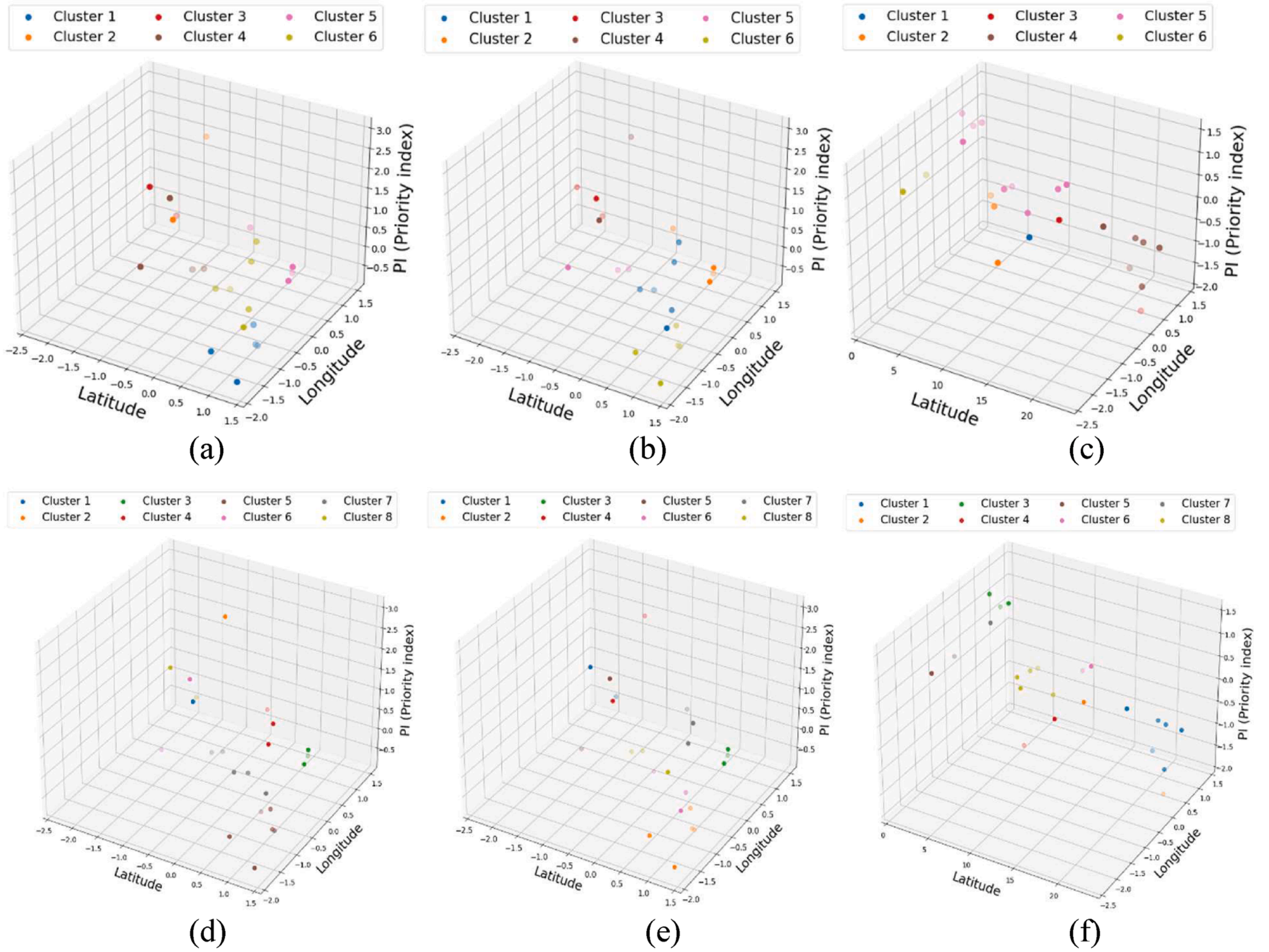


Fig. 7. Distribution of standardized a) social, b) environmental and c) economic sustainability indices of UASs.

Yue et al. (2010) presented the analysis of polycentric urban expansion in Hangzhou, China, focused on development clustered around economic activities.

Finally, the interrelationship between food security and environmental sustainability in a scaling-up process with regards to the UASs in each cluster can be observed by a cumulative context. By highlighting the clustering analysis of S2 a demonstration was presented in Fig. 10 based on the data set in Fig. 6(a) where this interrelationship is visualized through a logistic pattern globally. Although the FCI, WF and CF increase with the addition of more UASs to the network in a scaling-up



(a) (b) (c)

(d) (e) (f)

Fig. 8. Visual comparison of clusters in 3D feature space for scenario 1, scenario 2, and scenario 3: (a), (b), and (c) k = 6; (d), (e), and (f) k = 8; (g), (h), (i) k = 10; and (j), (k), (l) k = 12.

process, the cumulative approach with increased number of UAS integration confirms the contribution of clustering analysis which pull in the most sustainable clusters into the network in the beginning stage stepwise. It is evidenced by the fact that the transition between the addition of UASs from Cluster 7 to Cluster 8 with not much difference in terms of sustainability level is noted in the end. Although there is an increase in the trend from the beginning stage there seems to dampen and level off after the incorporation of Cluster 7.

3.3. *Multicriteria Decision-Making*

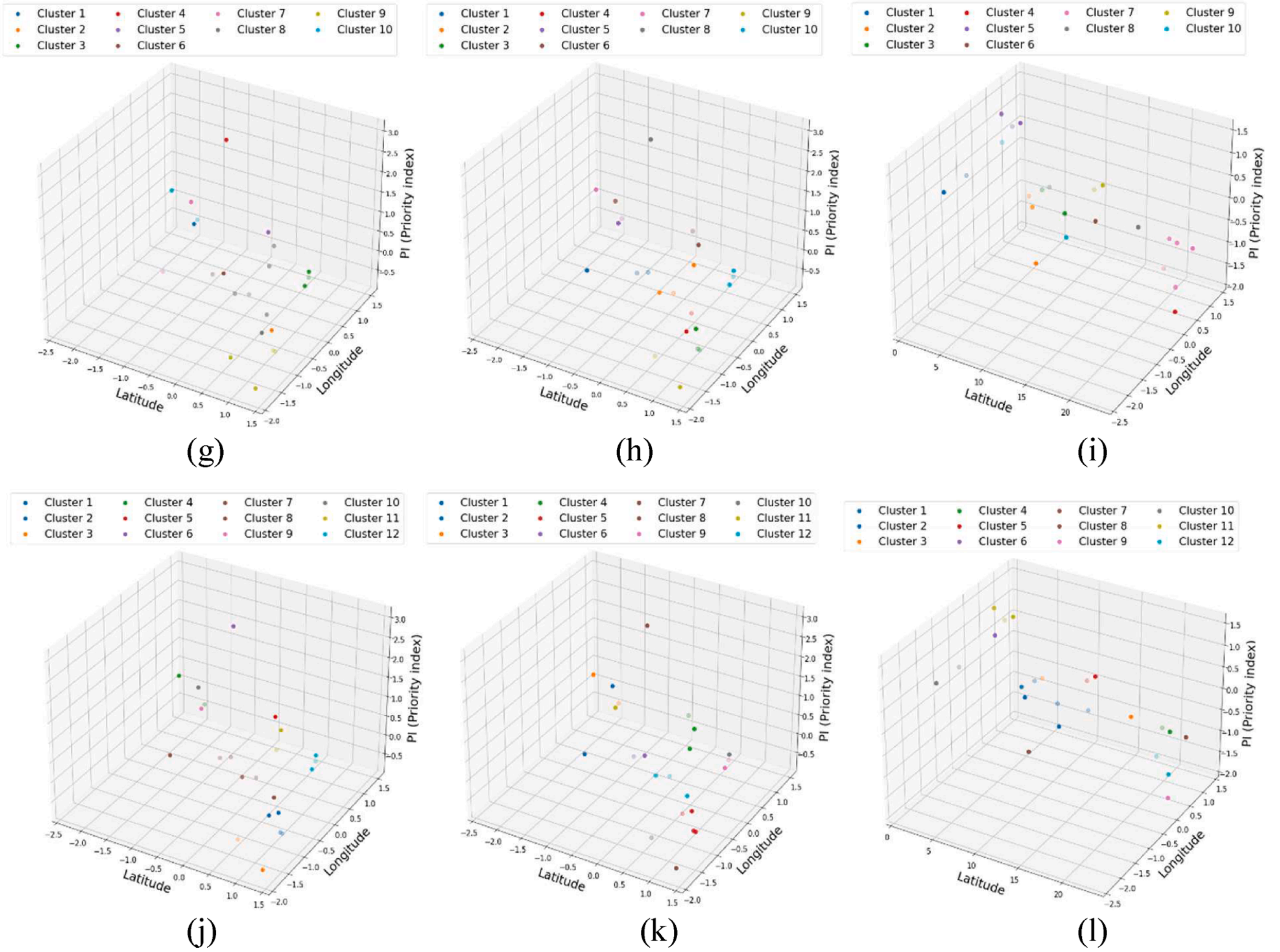
The MCDM approach was performed from the calculated PI pertaining to priority because of the higher vulnerability in the UAS clusters. For demonstration, k-cluster = 8 was selected for final MCDM to rank the clusters from the most to the least vulnerable to determine the priority for the three scenarios (Table 4). In the equal sustainability scenario (S1), where equal importance was placed on the sustainability indices, the integration of UAS clusters from highest to least priority is as follows: Cluster 2 → Cluster 1 → Cluster 4 → Cluster 6 → Cluster 5 → Cluster 8 → Cluster 7 → Cluster 3. In the climate prioritization scenario (S2), the UASs that have higher priority are Cluster 4 and Cluster 7, as opposed to S1, where Cluster 7 was one of the last ranked.

Although the economic prosperity scenario (S3) laid importance on economic gain from local food production and water reuse potential, both Cluster 2 and Cluster 4 were ranked as high priority. Further, because the implementation of the UAN is reliant on stakeholder decision-making, the scenarios can be ranked using TOPSIS to help identify which process for upscaling UAN shall be followed for the implementation of the UASs in the clusters. Considering all of the sustainability indices and the highest score alternative (P_i), S2 ranked the highest, followed by S3, and therefore, we suggest that the proposed UAN should follow S2 (Table 5). In this scenario, all sustainability indices are given higher priority due to climate change in the decision-making context.

4. Discussion

The UN SDGs goal-setting agenda draws on the efforts of sustainable development with the implication of governance strategies. Although creating sustainable cities and communities is the aim of SDG 11, other SDGs can be examined simultaneously. For instance, SDG 17 emphasizes the importance of cooperation and global partnerships at the local, national, and regional levels with two of SDG 17′s targets (17.16 and 17.17) aimed at strengthening and encouraging multistakeholder partnership for sustainable development as well as enhancing policy consistency for sustainable development (UN, 2020).

Yet the vague target descriptions in the SDGs provide room for interpretation and can lead to poor implementation (Biermann et al., 2017). The assessment of sustainability indicators as illustrated in this paper is able to provide stakeholders and decision-makers with



(g) (h) (i)

(j) (k) (l)

Fig. 8. (*continued*).

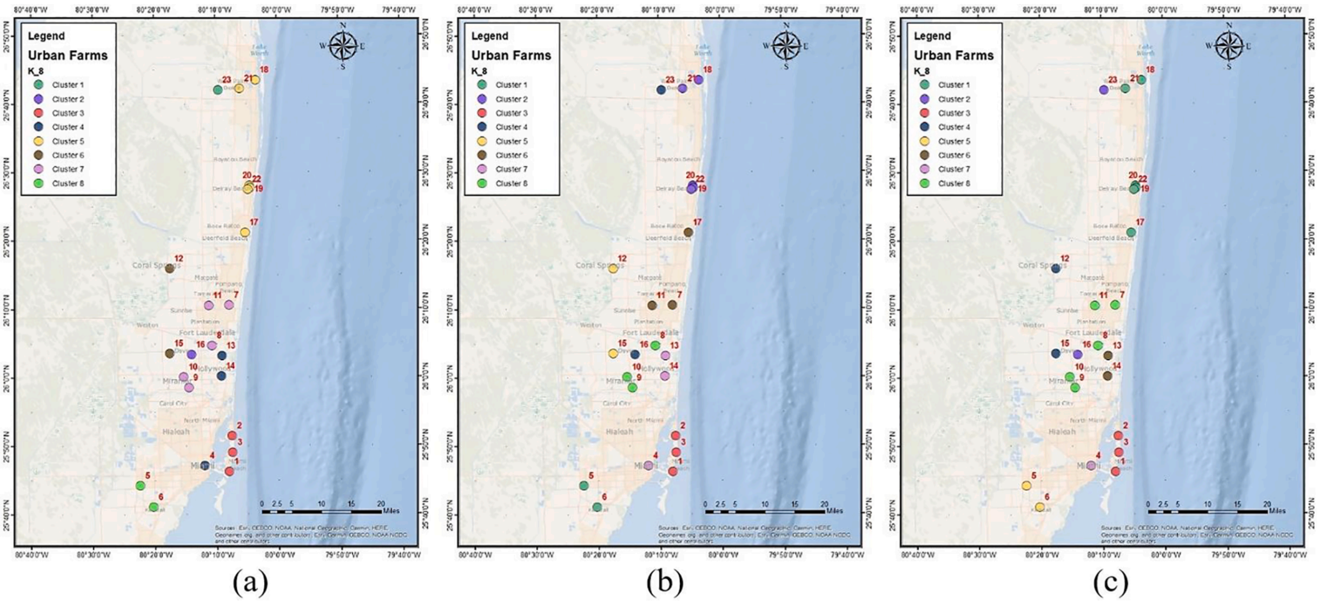
Table 3
Summary of clustering (k = 8) of UASs for three scenarios.

	Scenario 1		Scenario 2		Scenario 3
Cluster number	UAS	Cluster number	UAS	Cluster number	UAS
1	23	1	5	1	17
2	16		6		18
3	1	2	18		19
	2		19		20
	3		20		21
4	4		21		22
	13		22	2	16
	14	3	1		23
5	17		2	3	1
	18		3		2
	19	4	16		3
	20		23	4	12
	21	5	12		15
	22		15	5	5
6	12	6	7		6
	15		11	6	13
7	7		17		14
	8	7	4	7	4
	9		13	8	7
	10		14		8
	11	8	8		9
8	5		9		10
	6		10		11

sustainable pathways, as is the case of the City Sustainability Index presented by Mori and Christodoulou (2012a). Besides, the participation and engagement of decision-makers in the conceptualization and generation of sustainable development indicators is important to show their assessment potential across different site conditions (Mascarenhas et al., 2010). The methods of governance for sustainable development form strategies for functionalizing sustainable development (van Zeijl-Rozema et al., 2008). Hence, Kapucu et al. (2021) addressed stakeholder engagement and partnership in the food–energy–water nexus toward SDG implementation.

The emphasis of networks of organizations or partnerships (e.g., agencies) is important for addressing the implementation of sustainability goals. Network science is composed of the analysis of networks in various disciplines, such as information science, computer science, social network analysis, physics, and mathematics (Börner et al., 2007). Multiorganizational governance can also be perceived as a form of network (Provan et al., 2008). Thus, the governance structure is essential to the interaction of organizations, agents, and stakeholders in complex decision-making. A polycentric governance system is an approach to creating multiple independent governing entities (Feldman, 2016) as necessary for achieving collective sustainability. For instance, the crime rate can be linked to social equity in a cyclic pattern given that key factors in influencing crime rates include education levels and racial and ethnic backgrounds. Further, the crime rate can indirectly affect economic growth (Kusuma et al., 2019), which can be linked to income inequality and unemployment.

Yet this observation also applies to the structure of renewable energy



(a) (b) (c)

Fig. 9. Location of UASs from clustering analysis (k = 8): a) scenario 1, b) scenario 2, c) scenario 3.

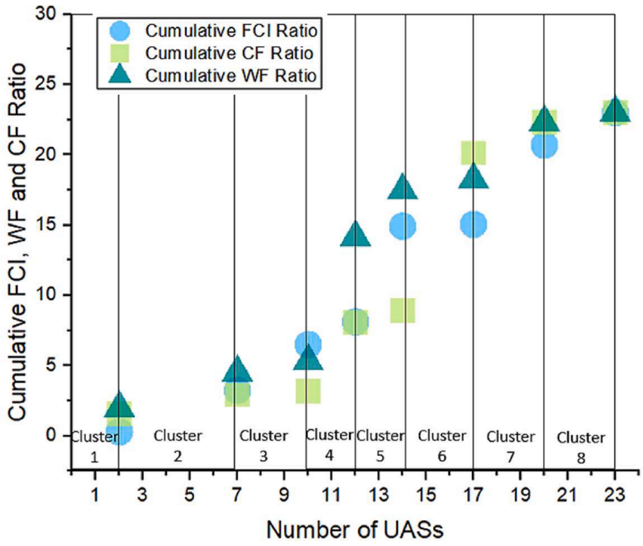


Fig. 10. Comparison of cumulative FCI, WF, and CF ratios among UAN clusters for Scenario 2 (S2) clustering analysis.

Table 4
Ranking of UASs based on priority index.

	Scenario 1	Scenario 2	Scenario 3
Rank of PI	Cluster number	Cluster number	Cluster number
1	2	4	2
2	1	7	4
3	4	5	6
4	6	2	1
5	5	1	5
6	8	6	8
7	7	3	7
8	3	8	3

Table 5
TOPSIS Multicriteria decision-making results.

Scenarios	S_i^+	S_i^-	P_i
Scenario 1	0.953	0.472	0.332
Scenario 2	0.975	0.951	0.494
Scenario 3	1.000	0.837	0.456

due to a variety of alternatives with respect to different technologies, which hinders cost-effectiveness while transitioning to the next stage for better sustainable development (Sanderink, 2020). Therefore, the governance structure has a key role in the implementation of relevant policies, such as in the case of Florida with the integration of an urban food–energy–water nexus as described in Table 6. This is intimately associated with water sources (e.g., groundwater, city water, stormwater, reclaimed water) and energy sources (e.g., utility grid and renewable energy) that require collective actions and interorganizational coordination between governance and institutional structures.

However, at present, there are no broad or general guidelines, strategies, or policies for sustainable development in the United States (Kapucu & Beaudet, 2020; Kapucu et al., 2021). Therefore, Kapucu and

Table 6
Subsidizes and grants in governance structure.

Food	Description	Energy	Description
Florida farm subsidies	Subsidies specific to crops (peanut, sugar, cotton) include price loss coverage, market assistance, quota buyout, and agricultural risk coverage	Federal Solar Investment Tax Credit (ITC)	Promote renewable energy, specifically solar energy, providing a 26 % tax credit for residential and commercial solar power systems
Environmental quality incentives program	Provides financial assistance to agricultural producers to preserve surface water and groundwater sources, improve air and water quality, and reduce soil erosion	Solar System Property Tax Exemption	Property tax exemption on the additional home value from the solar system
		Home solar system sales tax exemption	Tax exemption for residential solar system installation

Beaudet (2020) evaluated the existing structure and governing process for SDG implementation in a food–energy–water nexus context and emphasized the critical role of partnerships for the implementation of SDGs. To help a current UAN transition toward urban sustainability with an emphasis on planning via S2, the governance function entails the actions from governing authorities facing policies and incentives (e.g., local level) that promote social, economic, and environmental sustainability. Similarly, S1 can be described as a base scenario that does not need much effort via reshaping policies, such as generation of new policy instruments.

However, the results from S2 and S3 suggest how decision-making, governance, policy, and planning of UAN aimed at sustainability are interrelated and have a cascading effect. For example, the implementation of decentralized water management that can reduce the dependency of the current centralized system, such as decentralized wastewater treatment systems that are not connected to centralized sewer systems, can reshape the governance structure. Thus, stormwater reuse can further support and decrease the water demand specifically for the UASs with the highest WF (e.g., UAS16), which increases their sustainability. However, the inclusion of stormwater for irrigation requires adequate water quality standards regulated by policies that may require the cooperation between different agencies representing the water and food sectors. Further, as previously mentioned, to properly advance toward sustainable development and implement sustainable indices, it is crucial to also consider existing institutional and policy arrangements to establish the best next steps.

5. Conclusion

In this study, the evaluation of sustainability patterns via a series of environmental, social, and economic indices provides a means to quantify the priority of each UAS and helps policymakers foster a better governance program for these UASs. According to NASA-IPCC AR6 scenario SSP5-8.5 (low confidence) sea level rise projections of 2030 for a 300-meter delineation range it was found that UAS1, UAS 2, and UAS3 will be affected with flooding. Given the current understanding in governance and policy, MCDM assessment was incorporated into the clustering analysis to help visualize the clustering structures of the UAN and to rank them in accordance with the greater need for improvement or the level of social vulnerability. In scenario 1, where equal importance was emphasized in these sustainability indices the ranking of UAS clusters from the highest priority to the lowest ones for transition is as follows: Cluster 2 → Cluster 1 → Cluster 4 → Cluster 6 → Cluster 5 → Cluster 8 → Cluster 7 → Cluster 3.

In general, UAS2 and UAS4 were ranked the highest across the three decision-making scenarios; however, other variables (e.g., that dive further into the socioeconomic aspect) can be assessed to explore what differentiates these UASs from the rest in the UAN. This may require a more substantive approach to better understand the current demographics at the regions where the UASs are located as well as the urban agriculture strategies employed at each farm. With collation of large-scale datasets, the study highlights the contributions of UAN to urban sustainability through a food-water-energy nexus given governance structures that ultimately help achieve SDGs. We anticipate that our approach can be used to manage any high-dimensional UAN in different urban environments. Future work can be expanded to encompass an evaluation of the decision-making process for UASs in the Miami metropolitan area using innovative technology hubs to promote urban agriculture in an urban food–energy–water nexus.

CRediT authorship contribution statement

Andrea Valencia: Formal analysis, Resources, Software, Investigation, Validation, Visualization, Writing – original draft. **Jiangxiao Qiu:** Data curation, Conceptualization, Writing – review & editing. **Ni-Bin Chang:** Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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References

110th Congress, 2008. Food, Conservation, and Energy Act of 2008. p. 394.

Abidin, M.Z., Rusli, R., Shariff, A.M., 2016. Technique for order performance by similarity to ideal solution (topsis)-entropy methodology for inherent safety design decision making tool. Procedia Eng. 148, 1043–1050.

Adger, W.N., Brown, K., Fairbrass, J., Jordan, A., Paavola, J., Rosendo, S., Seyfang, G., 2003. Governance for sustainability: towards a 'thick'analysis of environmental decisionmaking. Environ. Plann. A 35 (6), 1095–1110.

ADT, 2019. Crime Map. https://www.adt.com/crime.

Astapov, S., Riid, A., 2015. A multistage procedure of mobile vehicle acoustic identification for single-sensor embedded device. Int. J. Electron. Telecommun. 59 (2), 151–160.

Astleithner, F., Hamedinger, A., Holman, N., Rydin, Y., 2004. Institutions and indicators–The discourse about indicators in the context of sustainability. J. Housing Built Environ. 19 (1), 7–24.

Ball, S., 2020. Farm on a Paris rooftop: Urban farm aims to be Europe's largest, France24.

Bank, W., 1992. Governance and development. The World Bank.

Behzadian, M., Otaghsara, S.K., Yazdani, M., Ignatius, J., 2012. A state-of the-art survey of TOPSIS applications. Expert Syst. Appl. 39 (17), 13051–13069.

Biermann, F., Kanie, N., Kim, R.E., 2017. Global governance by goal-setting: the novel approach of the UN Sustainable Development Goals. Curr. Opin. Environ. Sustain. 26, 26–31.

Blanchard, T.C., Matthews, T.L., 2007. Retail concentration, food deserts, and food-disadvantaged communities in rural America, Remaking the North American food system: Strategies for sustainability. pp. 201-215.

Börner, K., Sanyal, S., Vespignani, A., 2007. Network science. Annu. Rev. Inf. Sci. Technol. 41 (1), 537–607.

Broitman, D., Czamanski, D., 2015. Bursts and avalanches: the dynamics of polycentric urban evolution. Environ. Plann. B: Plann. Des. 42 (1), 58–75.

Brummelman, J., Haftmann, C., Nunez, N.G., Alvisi, G., Mazza, E., Becher, B., Lugli, E., 2019. Development, application and computational analysis of high-dimensional fluorescent antibody panels for single-cell flow cytometry. Nat. Protoc. 14 (7), 1946–1969.

C40 Cities, 2020. C40 Annual Report 2020.

C40, 2014. Climate Action in Megacities: C40 Cities Baseline and Opportunities.

Chikumbo, O., Granville, V., 2019. Optimal clustering and cluster identity in understanding high-dimensional data spaces with tightly distributed points. Mach. Learning Knowledge Extraction 1 (2), 715–744.

Chow, L., 2016. Inside Europe's Largest Urban Farm. https://www.ecowatch.com/inside-europes-largest-urban-farm-1891126795.html#toggle-gdpr.

Davidson, K., Gleeson, B., 2015. Interrogating urban climate leadership: Toward a political ecology of the C40 network. Global Environ. Politics 15 (4), 21–38.

Dempsey, N., Bramley, G., Power, S., Brown, C., 2011. The social dimension of sustainable development: Defining urban social sustainability. Sustain. Dev. 19 (5), 289–300.

Division of Food Safety, F., 2021. Cottage Foods. https://www.fdacs.gov/Business-Services/Food/Food-Establishments/Cottage-Foods.

Dutko, P., Ver Ploeg, M., Farrigan, T., 2012. Characteristics and influential factors of food deserts.

économiques, O.d.c.e.d.d., Nations, F.a.A.O.o.t.U., Fund, U.N.C.D., 2016. Adopting a territorial approach to food security and nutrition policy. OECD Publishing, Paris.

Escribano, G., 2015. Fragmented energy governance and the provision of global public goods. Global Policy 6 (2), 97–106.

European Commission, 2020. Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL on establishing the framework for achieving climate neutrality and amending Regulation (EU) 2018/1999 (European Climate Law). Brussels.

Harpke Family Farm, 2022. https://harpkefamilyfarm.com/.

Feldman, D., 2016. Polycentric Governance.

Florida Department of Agriculture and Consumer Servises, F., 2020. Cottage Food Operations, in: Florida Department of Agriculture and Consumer Servises, F. (Ed.).

Fuller, J., Muir-Cochrane, E., Lawn, S., Reed, R., Dawson, S., Oster, C., O'Kane, D., Henderson, J., Gerace, A., McPhail, R., 2015. Together for the mental health care of older people (TMOP) Improving the network planning and management of older people (TMOP): Improving the network planning and management of integrated primary mental health care for older people in rural regions. School of Nursing & Midwifery Flinders University.

Goldthau, A., 2014. Rethinking the governance of energy infrastructure: Scale, decentralization and polycentrism. Energy Res. Social Sci. 1, 134–140.

Grimes, K., 2021. California's New Crime Math Alters FBI 2020 Crime Data Showing Murder Rate Increased 30%, California Globe.

Guo, L.J., Haigh, J., 1994. A three-dimensional feature space iterative clustering method for multi-spectral image classification. Remote Sensing 15 (3), 633–644.

Hinneburg, A., Keim, D.A., 1999. Optimal grid-clustering: Towards breaking the curse of dimensionality in high-dimensional clustering.

Hodson, M., Marvin, S., 2009. Urban ecological security': a new urban paradigm? Int. J. Urban Regional Res. 33 (1), 193–215.

Holman, N., 2009. Incorporating local sustainability indicators into structures of local governance: a review of the literature. Local Environ. 14 (4), 365–375.

Holmes, D., 2020. Thammasat University – the largest urban rooftop farm in Asia. https://worldlandscapearchitect.com/thammasat-university-the-largest-urban-rooftop-farm-in-asia/.

Husgafvel, R., Pajunen, N., Virtanen, K., Paavola, I.-L., Päällysaho, M., Inkinen, V., Heiskanen, K., Dahl, O., Ekroos, A., 2015. Social sustainability performance indicators–experiences from process industry. Int. J. Sustain. Eng. 8 (1), 14–25.

IPCC, 2021. Climate Change 2021: The Physical Science Basis Summary for Policymakers, Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change, Cambridge University Press.

Ives, A., 2015. Neoliberalism and the concept of governance: Renewing with an older liberal tradition to legitimate the power of capital. Mémoire, identité, marginalité dans le monde occidental contemporain. Cahiers du MIMMOC 14.

Kapucu, N., Beaudet, S., 2020. Network governance for collective action in implementing United Nations sustainable development goals. Admin. Sci. 10 (4), 100.

Kapucu, N., Beaudet, S., Chang, N.-B., Qiu, J., Peng, Z.-R., 2021. Partnerships and network governance for urban food-energy-water (FEW) nexus. Int. J. Publ. Admin. 1–14.

Kloosterman, R.C., Lambregts, B., 2001. Clustering of economic activities in polycentric urban regions: the case of the Randstad. Urban Stud. 38 (4), 717–732.

Kong, Y., Wu, J., Yang, G., Zuo, Y., Chen, Y., Shu, H., Coatrieux, J.L., 2019. Iterative spatial fuzzy clustering for 3D brain magnetic resonance image supervoxel segmentation. J. Neurosci. Methods 311, 17–27.

Kusuma, H., Hariyani, H.F., Hidayat, W., 2019. The Relationship Between Crime and Economics Growth in Indonesia. KnE Social Sciences, 1105–1113-1105–1113.

Lang, S., Rothenberg, J., 2017. Neoliberal urbanism, public space, and the greening of the growth machine: New York City's High Line park. Environ. Plann. A: Econ. Space 49 (8), 1743–1761.

Mascarenhas, A., Coelho, P., Subtil, E., Ramos, T.B., 2010. The role of common local indicators in regional sustainability assessment. Ecol. Ind. 10 (3), 646–656.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., J.B.R. Matthews, Maycock, T.K., Waterfield, T., Yelekçi, O., Yu, R., Zhou, B., 2021. IPCC, 2021: Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change IPCC, Intergovernmental panel on climate change.

Mateo, J.R.S.C., 2012. Multi-criteria analysis, Multi criteria analysis in the renewable energy industry. Springer 7–10.

Mayer, A.L., 2008. Strengths and weaknesses of common sustainability indices for multidimensional systems. Environ. Int. 34 (2), 277–291.

Moreno-Pires, S., Fidélis, T., 2012. A proposal to explore the role of sustainability indicators in local governance contexts: The case of Palmela, Portugal. Ecol. Ind. 23, 608–615.

Mori, K., Christodoulou, A., 2012. Review of sustainability indices and indicators: Towards a new City Sustainability Index (CSI). Environ. Impact Assess. Rev. 32 (1), 94–106.

NASA, 2022. IPCC AR6 Sea Level Projection Tool. https://sealevel.nasa.gov/ipcc-ar6-sea-level-projection-tool.

National Academies of Sciences, E., Medicine, 2016a. Principles of Urban Sustainability: A Roadmap for Decision Making, Pathways to urban sustainability: challenges and opportunities for the United States. National Academies Press, pp. 27-39.

Németh, B., Molnár, A., Bozóki, S., Wijaya, K., Inotai, A., Campbell, J.D., Kaló, Z., 2019. Comparison of weighting methods used in multicriteria decision analysis frameworks in healthcare with focus on low-and middle-income countries. J. Comp. Eff. Res. 8 (4), 195–204.

Nguyen, H., 2018. Sustainable Food Systems Concept and Framework. Food Agriculture Organization of the United Nations, Rome, Italy.

Nikulina, V., Baumann, H., Simon, D., Sprei, F., 2018. Sustainable transport futures: Analysis of the selected methodologies supporting the planning process towards achieving goal 11 sustainable cities and communities, Handbook of Sustainability Science and Research. Springer 473–488.

Odu, G., 2019. Weighting methods for multi-criteria decision making technique. J. Appl. Sci. Environ. Manage. 23 (8), 1449–1457.

Popovitch, T., 2017. Nine of America's Largest Urban Farms. http://seedstock.com/2017/07/17/nine-of-americas-largest-urban-farms/.

Popp, J., MacKean, G., Casebeer, A., Milward, H.B., Lindstrom, R.R., 2013. Inter-organizational networks: A critical review of the literature to Inform practice. Alberta Centre for Child, Family and Community Research.

Provan, K.G., Kenis, P., 2008. Modes of network governance: Structure, management, and effectiveness. J. Publ. Admin. Res. Theory 18 (2), 229–252.

Provan, K.G., Kenis, P., theory, 2008. Modes of network governance: Structure, management, and effectiveness. Journal of public administration research and theory 18(2), 229-252.

Pupphachai, U., Zuidema, C., 2017. Sustainability indicators: A tool to generate learning and adaptation in sustainable urban development. Ecol. Ind. 72, 784–793.

Radzi, A., 2018. The 100% renewable energy metropolis: governing the design of cities for renewable energy infrastructures. Urban Energy Trans. Elsevier 85–113.

Rondelez, R., 2018. Governing cyber security through networks: an analysis of cyber security coordination in Belgium. Int. J. Cyber Criminol. 12 (1), 300–315.

Sanderink, L., 2020. Shattered frames in global energy governance: Exploring fragmented interpretations among renewable energy institutions. Energy Res. Social Sci. 61, 101355.

Sasaki, 2021. New model for urban farming for the world's largest agricultural producer and consumer: China. https://www.sasaki.com/projects/sunqiao-urban-agricultural-district/.

Shen, L.-Y., Ochoa, J.J., Shah, M.N., Zhang, X., 2011. The application of urban sustainability indicators–A comparison between various practices. Habitat Int. 35 (1), 17–29.

Talan, A., Tyagi, R., Surampalli, R.Y., 2020. Social dimensions of sustainability, in: Surampalli, R., Zhang, T., Goyal, M.K., Brar, S., Tyagi, R. (Eds.), Sustainability: Fundamentals and Applications. pp. 183-206.

Tanguay, G.A., Rajaonson, J., Lefebvre, J.-F., Lanoie, P., 2010. Measuring the sustainability of cities: An analysis of the use of local indicators. Ecol. Ind. 10 (2), 407–418.

Tasdemir, C., Gazo, R., Quesada, H.J., 2020. Sustainability benchmarking tool (SBT): Theoretical and conceptual model proposition of a composite framework. Environ. Dev. Sustain. 22 (7), 6755–6797.

UKCOP26, 2021. COP26 Goals. https://ukcop26.org/cop26-goals/.

UN, 2020. Goal 17: Revitalize the global partnership for sustianable development. https://www.un.org/sustainabledevelopment/globalpartnerships/.

United Nations, 2018b. SUSTAINABLE DEVELOPMENT GOAL 11: Make cities inclusive, safe, resilient and sustainable. https://sdg-tracker.org/cities.

United Nations, 2018a. 2018 Revision of World Urbanization Prospects, in: Affairs, D.o. E.a.S. (Ed.).

United States Census Bureau, 2022. 2109: DP03 SELECTED ECONOMIC CHARACTERISTICS.

United States ZIp Codes, 2022. Stats and Demographics. https://www.unitedstateszipcodes.org/.

Urban Farming Institute, 2022. About Us. http://www.ufi.us.org/about/.

USDA, 2021. Low income and low access, Food Acess Research Atlas. USDA.

USDL, 2022. REGIONAL AND STATE UNEMPLOYMENT — 2021 ANNUAL AVERAGES, in: Labor, U.S.D.o. (Ed.). Bureau od Labor Statistics,.

van Zeijl-Rozema, A., Cörvers, R., Kemp, R., Martens, P., 2008. Governance for sustainable development: a framework. Sustain. Dev. 16 (6), 410–421.

Verma, P., Raghubanshi, A., 2018. Urban sustainability indicators: challenges and opportunities. Ecol. Ind. 93, 282–291.

Wang, S., Liu, Y., Zhi, W., Wen, X., Zhou, W., 2020. Discovering urban functional polycentricity: a traffic flow-embedded and topic modeling-based methodology framework. Sustainability 12 (5), 1897.

World Health Organization, W., 2003. Diet, nutrition, and the prevention of chronic diseases: report of a joint WHO/FAO expert consultation. World Health Organization.

Wu, D., Wang, J., Lu, Y., Zhao, Y., 2018. Multi-attribute gray clustering decision based on three parameter interval number, 2018 Chinese Control And Decision Conference (CCDC). IEEE 2050–2055.

Yue, W., Liu, Y., Fan, P., 2010. Polycentric urban development: the case of Hangzhou. Environ. Plann. A 42 (3), 563–577.