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Research, part of a Special Feature on Panarchy: the Metaphor, the Theory, the Challenges, and the Road Ahead

Blurring the boundaries: cross-scale analyses of food systems

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ABSTRACT. The globalized and interconnected nature of food systems provides many examples of panarchies within social-ecological systems. However, few are analyzed using panarchy theory, particularly urban food systems, or in a comparative manner. We aimed to broaden the examination of cross-scale dynamics of food systems by applying panarchy theory through comparative study of three urban food systems: Flint, Michigan, Cleveland, Ohio, and Pittsburgh, Pennsylvania. These are all post-industrial Rust Belt cities that have experienced similar economic downturns but have responded in different ways, which has created significantly different food system outcomes. We present an approach for applying panarchy theory in food systems, and identifying indicators of potential and connectedness at multiple scales with sources for such data. We analyzed available data and demonstrate how the economic history of these cities has influenced their food system outcomes today. Economic recovery at the city scale in Pittsburgh/Allegheny County was reflected in reorganization in the food system, while the lack of economic recovery in Flint/Genesee County and the uneven access to economic recovery in Cleveland/Cuyahoga County potentially placed the cities and their food systems in lock-in traps. We also reflect on the limitations of publicly available data at the city scale for the food system and over time. Overlooking such gaps may blur boundaries within a panarchy analysis and lead to assumptions about cities based on county data which might not be accurate or may hide critical variables such as race or geographic size. We caution researchers to be clear about scale in panarchy analyses and to acknowledge the limitations of current data sets and thus the importance of mixed methods primary data collection. The incorporation of place and historical context into panarchy analyses can lend valuable explanatory power to our understanding of cross-scale dynamics in food systems.

Key Words: *connectedness; food systems; potential; Rust Belt; urban*

INTRODUCTION

Understanding cross-scale dynamics is a critical component of analyzing food systems from a social-ecological resilience perspective. Panarchy describes the existence of systems in a nested, interconnected hierarchy in various stages of growth, collapse, innovation, and reorganization (Gunderson and Holling 2002), and thus provides a framing to explore these cross-scale dynamics but is rarely operationalized to do so. Previously, we used resilience assessment (Resilience Alliance 2010) to identify panarchy dynamics using a mix of qualitative and quantitative data from a community-engaged research project in Flint, Michigan (Hodbod and Wentworth 2022). Drawing on this work, we aimed to broaden our examination of cross-scale interactions on the resilience of food systems by including two additional Rust Belt cities—cities in the U.S. Midwest that were once dominated by industry (Dieterich-Ward 2015). Our original goal was to use panarchy to examine distinctions in the post-war history of these cities and analyze what led to the different food systems regimes today. We designed a comparative study of the cross-scale dynamics of the Flint, Michigan, Cleveland, Ohio, and Pittsburgh, Pennsylvania food systems using a panarchy framing. These post-industrial cities experienced similar effects of industrial decline, depopulation, and economic hardship, the effects of which resulted in significantly different food system outcomes. Our original aim was to draw on secondary data to compare how food systems within each city evolved after deindustrialization and how they then responded to crises in order to identify releases and reorganizations that influence the food system.

Through this work, we demonstrate that data essential to understanding food systems are currently collected at differing scales, but rarely the city scale. Frequently, data are presented at a county scale, and researchers, when comparing data, make assumptions about underlying similarities between cities and the counties in which they are located. However, those broader assumptions ignore significant differences between cities and their size and impact relative to the counties in which they reside. This led us to a significant, yet unexpected conclusion—the current data environment obscures the realities of food systems, particularly at the city scale. We highlight the ways that current data affect the ability of researchers to conduct effective cross-scale analyses, which often results in blurring the boundaries between city and county data and obscuring significant contextual information about the importance of scale and place in understanding food systems. Through a presentation of data from Flint, Pittsburgh, and Cleveland, we outline the data we intended to use to make cross-scale comparisons and highlight what distinctions we can draw between focal cities and their counties. This process illustrates ways in which food security data are collected that prevent accurate comparisons. Ultimately, using a panarchy framing reveals the effect of place on cross-scale analysis, underscores critical distinctions between city and county data, and provides important reframing for the study of food systems from a social-ecological perspective.

The Rust Belt—industrial decline and divergent recovery in Flint, Pittsburgh, and Cleveland

The Rust Belt is a section of the American Midwest near the Great Lakes that was once characterized by high industrial production and shipping but which suffered economically with industrial collapse. The metaphor links the rusting of old steel to economic downturn and decay experienced in the later 20th century across this region. To determine our sample, we chose three Rust Belt cities with similar histories of growth and achievement but very different food system outcomes today. For this research, site

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selection included cities that met the following criteria: once celebrated as hubs of industrial innovation, home to at least one major industrial company, home to at least one private philanthropic organization with assets over US$1 billion tied to families that profited from historical industry, periods of significant post-war economic and population growth followed by decline, and divergent narratives of recovery today. These criteria enabled us to focus on cities that were not dependent on a single industrial plant, that sprouted innovative development from parallel industries, and that engendered long-term commitment and investment from private philanthropic organizations (excluding universities and medical systems) that support urban engagement and are large enough to impact redevelopment efforts.

Located about 1 hour north of Detroit, Flint (Genesee County) is known as "Vehicle City" due to the central role it played in the development of the U.S. auto industry. Once one of America's richest cities, Flint experienced decades of decline due to the closure of several major General Motors plants and the resulting collapse of numerous supportive automotive industries (Clark 2018). The combination of industrial collapse, urban planning, such as the growth of expressways through the middle of the city, integration of schools, and development of low-income housing resulted in white flight as more affluent white residents left the city for the suburbs (Highsmith 2015). As a result, Flint lost nearly half its population and experienced a significant decrease in the median income and an increase in the poverty rate (Highsmith 2015). Today, the C.S. Mott Foundation holds US$3 billion in assets, and development of the Flint area is one of four priority areas.

Located about 45 minutes from the western border of Pennsylvania, Pittsburgh (Allegheny County) is known as the "Steel City" due to the central role that the steel industry played in the growth and development of wealth in the city. Pennsylvania faced periods of industrial decline since the 1920s; the 1980s were particularly difficult years, when the city lost more than 42% of its manufacturing jobs (Detrick 1999). With the closure of steel mills, the city refocused its development around the "eds and meds" economy; that is, supporting the growth of higher education institutions ("eds"), medical research, and an expansive hospital system ("meds") dominated by the University of Pittsburgh Medical Center (Dieterich-Ward 2015). Often this development required public–private partnerships for a collaborative model of redevelopment (Detrick 1999), which serves as an example of successful reorganization of post-industrial U.S. cities. However, the investment in redevelopment efforts often excluded Black neighborhoods, which, by the 1990s, left the social and economic conditions of the Black population among the worst in the United States (Detrick 1999). The Richard King Mellon Foundation holds US$2.2 billion in assets and seeks to support development of the Western Pennsylvania region, and specifically the city of Pittsburgh across six priority areas.

Located in north-central Ohio, on the shores of Lake Erie, Cleveland (Cuyahoga County) is known for rapid industrialization in the mid-1800s through the early 1900s and the growth of several major companies, including Standard Oil, Sherwin-Williams, and U.S. Steel. Cleveland was an early national leader in oil refinery, iron and subsequently steel production, and the manufacture of transportation equipment. By 1930, Cleveland was second in the nation, behind Detroit, in the percentage of the population employed by industry (Stapleton 2021). After decades of decline due to the closure of industrial plants and residents' reaction to severe environmental contamination, Cleveland began to restructure around major research institutes and related corporate industrial research laboratories (Stapleton 2021). However, this provided uneven growth, racial segregation by neighborhood, and pockets of persistent poverty (Coulton et al. 2010). The Jack, Joseph and Morton Mandel Foundation promotes urban engagement and neighborhood development as one of five priority areas, and holds US$1.7 billion in assets.

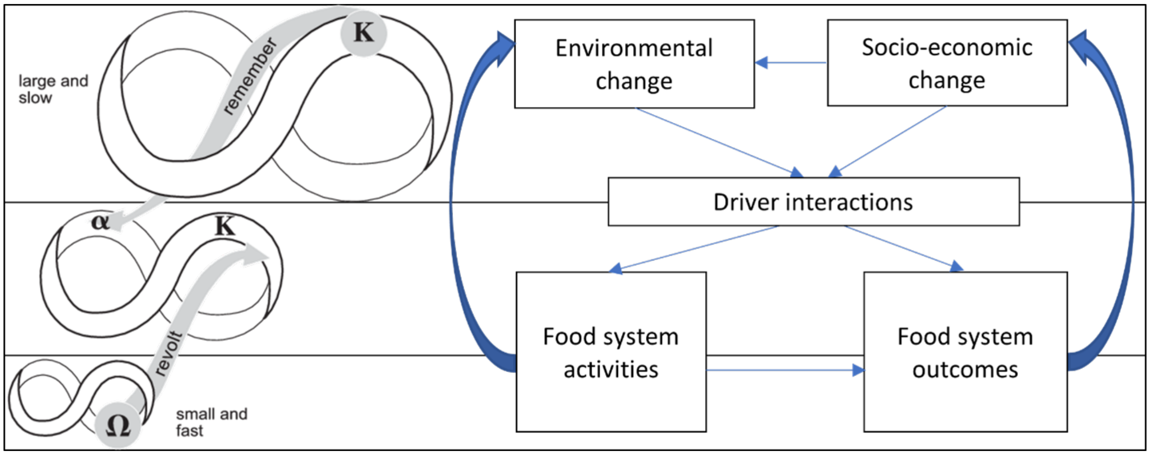
Flint, Cleveland, and Pittsburgh each played historic roles in leading the nation in industrial development, yet each city also faced similar periods of decline following the initial dismantling of its industrial base. Despite the parallels in industrial growth and decline, today each city is marked by divergent ideas of whether or not it has experienced successful economic recovery, which we outline in our results. It is for these reasons, and based on our experience with previous research in Flint and Pittsburgh, that these three cities were used as the focus of our analysis. Race plays a significant role in how residents of each city experienced decline and the level of inclusion in rebuilding efforts. We specifically acknowledge the disproportionate impact that racism, housing discrimination, and deliberate economic disenfranchisement had on Black residents in the past and how structural racism persists today. We argue that operationalizing panarchy allows us to explore how changes across food systems in Rust Belt cities relate to the broader socio-economic systems in which they are nested.

Cross-scale analyses of food systems

Food systems include the production, distribution, consumption, and waste of food, and are developed to achieve a fundamental human objective: individual biological sustenance (Hodbod and Eakin 2015). When applying a panarchy analysis, the first step is to define the focal scale. We consider the focal scale of a food system to be the spatial and temporal scale at which key food system activities occur. In city-scale analyses, we recognize that production often occurs outside the city limits; thus, urban food systems are simultaneously influenced by broader factors beyond the bounded system, which creates telecouplings and hierarchical relationships (Garrett and Rueda 2019). The globalized and interconnected nature of our food systems therefore provides many examples of panarchy within a social-ecological system (SES) framing. Our conceptual framing reveals that slower dynamics occur at larger scales (i.e., global environmental change and socio-economic drivers), and the focal scale influences a smaller scale (i.e., the household or individual demonstrating food security outcomes) (Fig. 1) (Drever et al. 2006, Ericksen 2008). Therefore, the cross-scale linkages highlighted in the heuristic of panarchy are especially useful for analyzing the dynamic nature of local, regional, and global food systems.

The literature on cross-scale dynamics documents a small but growing set of empirical studies that have used the adaptive cycle and panarchy, and mostly analyzed regime shifts within ecological (non-food) systems, and have used historical narratives to identify

Fig. 1. When considering how food systems demonstrate panarchical dynamics, we integrate the core elements of a food system to show the food system within a city as the focal (middle) scale. The smaller spatio-temporal scale reflects the household food system, and the broader institutional scales are reflected in the spatio-temporal scale above the focal scale. (Figure adapted from Drever et al. 2006 and Ericksen 2008; r indicates growth phase, K indicates conservation phase, omega indicates release phase, alpha indicates reorganization phase).



phase changes in the adaptive cycle at one scale, particularly to examine the overexploitation of natural resources (i.e., Walker et al. 1981, Beier et al. 2009, Soane et al. 2012). A subset of studies have used similar historical narratives to explore ecological dynamics within food systems (Fraser 2003, Allison and Hobbs 2004, McAllister et al. 2006, Fraser 2007, Dugmore et al. 2009, Moen and Keskitalo 2010, Rosen and Rivera-Collazo 2012, Perez Rodriguez and Anderson 2013, Stroink and Nelson 2013, Salvia and Quaranta 2015, Rawluk and Curtis 2016, Teuber et al. 2017, Jiménez et al. 2020). These studies apply the adaptive cycle and/or panarchy in one SES over time.

Simultaneously, there has been a recent emergence of adaptive cycle studies that have focused more on social change within SESs and have examined the dynamics of institutional arrangements or the influence of potential and connectedness on resilience. Most have been in urban (e.g., Herrmann et al. 2016) or conservation case studies (e.g., Baral et al. 2010). A small number of studies have applied the adaptive cycle to social subsystems within food systems, and have commonly examined how rural livelihoods change over time (Robinson 2009, Rasmussen and Reenberg 2012, Goulden et al. 2013, Thorkildsen 2014, Bollig 2016, Winkel et al. 2016). The communities studied were relatively small, in both population size and diversity of stakeholders, and had clearly defined boundaries. Few researchers apply panarchy theory to complex, urban food systems, which Hodbod and Wentworth (2022) began to address. There is, therefore, a gap in using (1) panarchy theory to understand change across comparative cases, and (2) large urban food systems with similar structure and function and yet different outcomes. Our work originally set out to apply panarchy theory to these types of cases.

Commonly, food systems are compared using standardized quantitative data sets (e.g., census, agricultural census, food security, and socio-economic indicators) to compare outcomes. As Ericksen (2008) showed, food system outcomes include food security (availability, access, utilization, and stability), social welfare, and environmental welfare. Food access as a form of food insecurity, "defined as a lack of consistent access to enough food for every person in a household to live an active, healthy life," is the primary food system outcome measured by Feeding America and the United States Department of Agriculture (Feeding America 2021). We consider food security as a social and economic condition and highlight that no single indicator is universally accepted as a full measure of food security. Thus, we present multiple related indicators to help us understand food insecurity and the impact it has on individuals and families. These outcomes are tracked at multiple scales and are analyzed both quantitatively and qualitatively because we believe there are limitations to the explanatory power of purely statistical analyses of food system outcomes. While correlation can be ascertained from these data, and causation to some extent (i.e., poor nutritional outcomes in young children and adults can be predicted by poverty rates [Bhattacharya et al. 2004]), additional context is needed to design sustainable, food-secure futures. We propose that a panarchy analysis can lend explanatory power to comparisons of complex, urban food systems and provide an interdisciplinary way of unpacking cross-scale interactions that determine system outcomes. Such an approach allows us to examine the food system in the context of broader systems and over time. In a novel application, we applied the panarchy framing to multiple city-scale food systems within the same analysis to explore how their different evolutions were influenced by cross-scale dynamics. A historical and cross-scale understanding of different food security outcomes across these cities today can then inform tipping points that move these cities to more food secure futures. However, this research revealed significant limitations in how data are collected, which affect our ability to understand cross-scale comparisons.

METHODS

As an extension of Resilience Alliance (2010) and Hodbod and Wentworth (2022), the first step of our analysis was to define the focal scale of the system prior to considering adaptive cycles and panarchy. This process (done first in collaboration with a Community Consultative Panel in Flint, Michigan that was assembled for our broader project [Hodbod and Wentworth 2022], and then by the researchers) outlined the comparison of Flint, Cleveland, and Pittsburgh food systems over the last 70 years, and focused on the post-World War II period to the present to capture periods when all cities experienced growth and subsequent decline.

Building on the original work by Holling and Gunderson (2002), Allison and Hobbs (2004) noted that if each of the three dimensions (potential, connectedness, and resilience) in the adaptive cycle is given two nominal levels, either low or high, then the adaptive cycle model uses only four of a possible eight combinations. The remaining combinations are suggested to be maladaptive states or traps (Table 1). By first understanding the dynamics of the adaptive cycle for the food system in each city, we can then explore the cross-scale dynamics that trigger iterations of the adaptive cycle.

Table 1. Different phases of the adaptive cycles have different levels of potential, connectedness, and resilience. There are four possible other combinations known as traps (departures from the adaptive cycle). The relative levels of potential, connectedness, and resilience for all eight phases are described, as per Holling and Gunderson (2002) and Allison and Hobbs (2004).

Phase	Potential	Connectedness	Resilience
α Reorganization	High	Low	High
r Exploitation	Low	Low	High
K Conservation	High	High	Low
Ω Release	Low	High	Low
Poverty trap	Low	Low	Low
Rigidity trap	High	High	High
Lock-in trap	Low	High	High
? trap	High	Low	Low

Building on Hodbod and Wentworth (2022), our approach was to identify the location of the system in a phase of the adaptive cycle or a trap by exploring relative levels of potential and connectedness over time using both qualitative and quantitative indicators (Holling and Gunderson 2002, Holling et al. 2002, Allison and Hobbs 2004). We first brainstormed a “long list” of possible indicators based on our understanding of the various types of capital within city-scale food systems (as the focal scale) but also household food systems and the broader city according to a panarchy framing. Capital is a stock or resource that yields a flow of valuable goods or services into the future, from which human well-being arises; our long list was arranged around the five types of capital (Costanza and Daly 1992). In our framing, natural, financial, physical, and human capital were used to assess system potential and social capital to determine system connectedness. Natural capital indicators across the scales included food security (categorized here to reflect food availability), pounds of food distributed through food assistance programs, number and type of food retail stores, and land under food production. Financial capital indicators in the food system demonstrated some overlap with broader city system indicators, including median income and poverty rates, because these in turn influence indicators such as reliance on school feeding programs. Physical capital indicators in the food system included bus routes, community meeting spaces, and food pantries, and population at the broader city scale. Human capital indicators included extension programs in production and nutrition. Social capital indicators at the food system scales included participation in federal food assistance programs (e.g., Electronic Benefits Transfer and Double Up Food Bucks) and grocery stores as a proportion of the population. At the broader city scale, indicators of connectedness included social networks, support networks, functions of institutions, and governance.

We then attempted to collect data for each indicator on the long list to establish what longitudinal data were available at each scale in each case study. Secondary data were elicited from peer-reviewed and gray literature (including the United States Department of Agriculture Food Access Atlas, the United States Census Bureau, Feeding America, and key organizations, such as food banks in each city). While quantitative data were prioritized, when they were unavailable, qualitative data were also used to describe longitudinal trends. However, we were not able to create a full data set for all indicators. Table 2 shows the “short list” of indicators with longitudinal data, in bold. It quickly became clear that few data existed at the city scale; most were available for the county scale. Without primary data collection, we could not establish perceptions of trends in these indicators from key stakeholders, as we had done previously in Flint when secondary data were lacking (Hodbod and Wentworth 2022). The limitations of this are discussed further, and for this reason, Table 2 also shows, in italics, the data that we felt would be critical yet were not available at the relevant scale.

The short list of indicators for which we had longitudinal data across all three case study sites was limited to food security outcomes at the county scale and socio-economic indicators at the household, city, and county scale. While this reflected both potential and connectedness, it changed the planned city-scale analysis to a combined city–county analysis, with the acknowledgement that county-scale data obscure the dynamics in each city. The steps for this analysis in Flint, with sufficient data at the city scale, are provided in Hodbod and Wentworth (2022).

Once the data set was identified and the focal scale was adjusted, we proceeded to situating the adaptive cycle dynamics of the food system within a broader socio-economic context via a panarchy framing. Informed by our literature review to provide historical context, we looked more broadly at the cross-scale dynamics, and the revolt and remember connections between scales. We looked for key events: internal or external shocks or disturbances that have the potential to influence structure and function of the city and could explain a release and reorganization in each city’s food system. Examples were also drawn from qualitative data, which included physical restructuring due to highway construction, closure of primary industry, and areas of major reinvestment or growth from new industry—essentially, events in each city’s

Table 2. Data collected to inform the panarchy analysis were incomplete—bold indicates successful data collection for all three case studies and the scale; italics indicate data that we thought were necessary but were not available at the city scale. Such data may be available in other cities for other researchers to use in similar analyses; therefore, we have included them as suggested potential sources. We also encourage future collection of city-scale data for these indicators so that these trends can be evaluated in the future.

	Potential	Source	Connectedness	Source
Household food system	**Median income raw and adjusted 2020 dollars**	**U.S. Census Bureau (2020b, c)**	*Supplemental Nutrition Assistance Program (SNAP) – recipient or not*	*Primary data collection*
	County average cost per meal	**Feeding America (2020)**	*Social networks*	*Primary data collection*
City/county/state food system	**Food security rate (***city,*** county, state)**	**Feeding America (2020)**	**SNAP – county issuance, number of households as proportion of county**	**U.S. Census Bureau (2020b, c), USDA FNS (2020)**
	Health outcomes – obesity (state), diabetes (county; city in 2017)	**CDC (2019, 2020), United Health Foundation (2020)**	**Grocery stores as proportion of the population**	**U.S. Census Bureau (2020a)**
	Emergency food access – number of food pantries, pounds of food	*Food banks; i.e., Food Bank of Eastern Michigan shared data, but data were not available from Greater Cleveland Food Bank and Greater Pittsburgh Community Food Bank*	*Governance of the food system – trust*	*Primary data collection, some existing in Flint*
	Natural capital – pounds of food/fresh fruits and vegetables, land for urban agriculture, Nutrition Environment Measures Survey		*Emergency food access – unique number of users*	*Not collected by all food banks*
	Financial capital – program funding (Double Up Food Bucks, school lunch feeding programs)	*USDA, food banks*	*Social capital – program enrollment (Double Up Food Bucks, school lunch feeding programs)*	*USDA, food banks*
	Human capital – number of education and extension services	*Primary data collection*	*Human capital – enrollment in education and extension services*	*Local education and extension organizations*
	Physical capital – number of food pantries, farmers markets, stores (number, quality [fresh fruits and vegetables])	*Food banks, economic census, primary data collection*	*Physical capital – transportation links to stores; number of people dependent on public transport for groceries*	*Local government records, primary data collection*
City/county broader social-ecological scale	**Population (race dynamics)**	**U.S. Census Bureau (2020b, c)**	*Governance of the city – trust*	*Primary data collection, some existing in Flint*
	Poverty rate	**U.S. Census Bureau (2020b, c)**		
	Vacant lots (urban agriculture)	*Land banks*		
	Physical capital – transport networks and public transport	*Primary data collection*		

history that marked significant social change. We concluded by analyzing the dynamics of the larger and smaller scales in the study.

The following is an analysis of available indicators from both quantitative and qualitative secondary sources and panarchical dynamics for each city. While limited, the data did allow for comparisons at city, county, and state scales and offered insight into the variation among the food systems of the cities, thereby demonstrating the utility of a panarchy framing.

RESULTS

The available data, as outlined in Table 2, are presented indicator by indicator for the three case studies, first for the broader city–county scale to provide data behind the historical context, and then for the food system. Trends across the three case studies are summarized for each indicator. At each scale, once all potential and connectedness indicators are presented, their patterns are synthesized to demonstrate adaptive cycle dynamics. Finally, the food system is situated within the context of the broader socio-economic conditions of the city to demonstrate cross-scale interactions and how they differed across the three cities.

City–county indicators – potential

Beginning with demographic data at the city scale as an indicator of potential, Table 3 shows longitudinal trends in population in all three cities (U.S. Census Bureau 2020b). Population also influences the potential of the food system directly via food availability because it impacts demand and consumption. There has been a significant urban decline in population since the post-war era but growth in the proportion of Black residents, which indicates that more white residents have left each city. These changes correspond to historical documentation of redlining and white flight that occurred in urban centers across the country (Nelson et al. 2021).

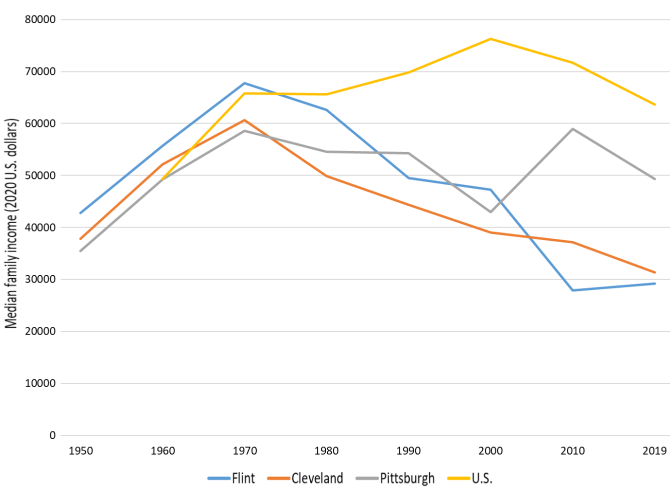
Because income influences food access, we also compared median family income for each city from 1950 to the present to capture the period of post-World War II growth across the United States (Tarasuk et al. 2019). Lagging slightly behind the patterns for

Table 3. Total, white, and Black population data for Flint, Cleveland, and Pitsburgh, 1940–2018 (U.S. Census Bureau 2020b). The population of Flint peaked a decade later than that of Cleveland and Pittsburgh (1960 compared to 1950), but all three cities showed an overall population decline associated with an increasing proportion of Black residents in the remaining population, which illustrates the effects of redlining and white flight.

	Flint				Cleveland				Pittsburgh			
Year	Total pop	White	Black	%Black	Total pop	White	Black	%Black	Total pop	White	Black	%Black
1940	151,543	144,858	6,599	4.35	878,336	793,417	84,504	9.62	671,659	609,235	62,215	9.26
1950	163,143	149,100	13,906	8.52	914,808	765,264	147,847	16.16	676,806	593,825	82,453	12.18
1960	196,940	162,128	34,521	17.53	876,050	622,942	250,818	28.63	604,332	502,593	100,692	16.66
1970	193,317	138,065	54,237	28.06	750,903	458,084	287,841	38.33	520,117	412,280	104,904	20.17
1980	159,611	89,647	66,124	41.43	573,822	307,264	251,347	43.80	423,938	316,694	101,813	24.02
1990	140,761	69,788	67,485	47.94	505,616	250,234	235,405	46.56	369,879	266,791	95,362	25.78
2000	124,943	51,710	66,560	53.27	478,403	198,510	243,939	50.99	334,563	226,258	90,750	27.12
2010	102,434	38,328	57,939	56.56	396,815	147,929	211,672	53.34	305,704	201,766	79,710	26.07
2018	95,932	37,069	51,902	54.1	383,781	158,228	181,840	47.38	301,038	202,511	68,867	22.88

population, median family income for residents in all cities continued to increase until about 1970 (U.S. Census Bureau 2020b). Median family income, presented in 2020 dollars (U.S. Bureau of Labor Statistics 2020), indicated that many residents maintained a living wage until the periods of significant plant closures and job loss associated with the end stages of industrial decline (Fig. 2). Significantly, the median family income across the United States continued to increase for much of the period after 1970, which reveals a distinction between wider U.S. growth and the relative impact of industrial closures on post-industrial Rust Belt cities.

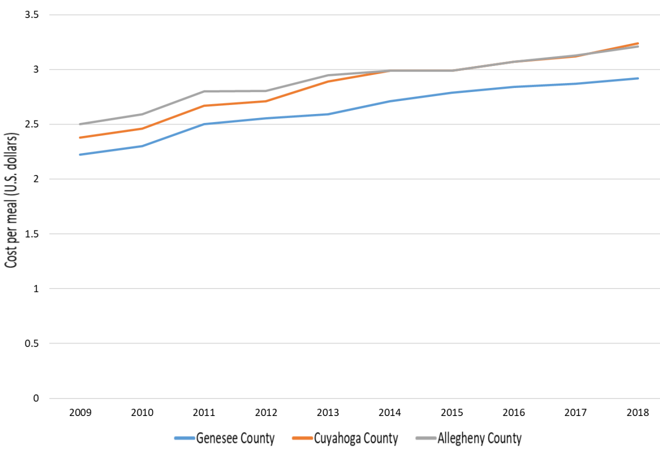
Fig. 2. Median family income across cities, 1950–2019, adjusted to 2020 U.S. dollars. From 2000 to 2019, median income was the lowest in Flint and increased in Pittsburgh. Results are presented as adjusted to 2020 dollars to allow city trends to be compared with the U.S. trend, which shows a distinction between Rust Belt cities and the United States as a whole (U.S. Bureau of Labor Statistics 2020).



Because the 2020 U.S. Census results were not published at the time of our research, we supplemented census data from 1950 to 2010 with the latest data from the annual American Community Survey to explore the most recent median income data. The median household income for a Flint resident (2015–2019, in 2020 U.S. dollars[1]) was just $29,212, and 38.8% of residents were living in poverty (U.S. Census Bureau 2020c). Flint's median income was the lowest of the three cities and was significantly lower than that of Genesee County, where median household income for the same period (2015–2019) was $49,349, and the poverty rate was 16.6%. In comparison, the U.S. median household income was $63,666, and 10.5% of the population was living in poverty (U.S. Census Bureau 2020c). In Cleveland, the median household income was $31,312 (in 2020 U.S. dollars), and 32.7% of residents were living in poverty; Cuyahoga County reported a median household income of $51,005 and 16.2% of residents living in poverty (U.S. Census Bureau 2020c). In Pittsburgh, the median household income was $49,349 (in 2020 U.S. dollars), and 20.5% of residents were living in poverty; Allegheny County reported $61,842 and 10.8%, respectively (U.S. Census Bureau 2020c). Poverty rates were not comparable to other geographic scales or over time due to methodology differences in the way these measures were defined and calculated (U.S. Census Bureau 2020c); therefore, they are not presented as longitudinal data. However, the combination of median income and poverty rate data demonstrated that all three counties and cities were behind the U.S. average (although Allegheny County was similar) and that the three cities were poorer than their respective counties.

The average cost of a meal (available through the "Map the Meal Gap" data set for 2009–2018 at the county scale [Feeding America 2020]) was used to provide context about household potential but provided insight into affordability and thus access to food. There was a similar upward trend across all three counties during this decade, but in Genesee County, the average cost of a meal was about 10% less than that in Cuyahoga and Allegheny Counties at all times (Fig. 3). When considered with median income, the residents of Cuyahoga and Genesee Counties had the lowest median household incomes and therefore least purchasing power and potential. Assuming the cost of meals at the city scale was comparable with the county average (data were not available at the city scale), food affordability would be even more difficult in Flint and Cleveland given that their median incomes were lower than those of their respective counties.

Fig. 3. Cost per meal (2009-2018) at the county level—this data is not available at the city level (Feeding America 2020). Genesee County's average cost per meal is about 10% below Cuyahoga and Allegheny's over the decade.



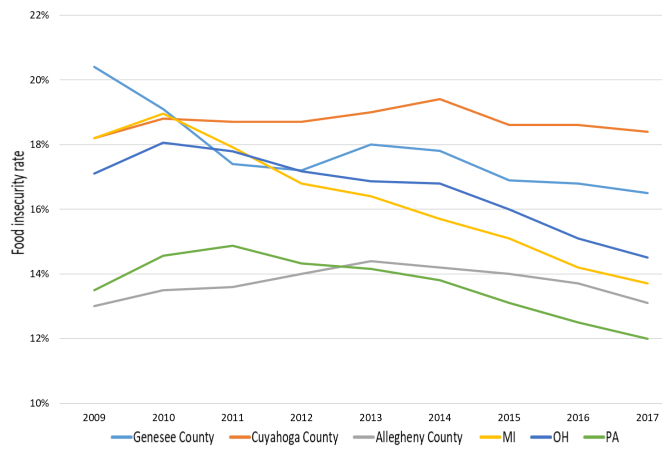
Adaptive cycle dynamics at the city–county scale

Data that measure potential allow us to begin to make some interpretations about the adaptive cycle dynamics at the city and county scales, as per relative levels of potential in each phase outlined in Table 1. In all cities, potential (similar to population and median income) increased through the 20th century to the 1960s and 1970s, indicating a shift from an exploitation (low potential) to conservation phase, which supported a (short-lived) relative high in potential in each city. A release and reorganization phase seems to have followed for Pittsburgh, with some recovery of median household income, but Flint and Cleveland appear not to have reorganized from their release, as indicated by low levels of current-day potential in comparison (as per median income, cost of average meal, population, and poverty rate). Without connectedness data, these interpretations are incomplete, particularly for Cleveland and Pittsburgh. However, a validity check of the analysis illustrated that the Flint analysis aligned with Hodbod and Wentworth (2022), which found the city of Flint to be in a lock-in trap (low potential, high connectedness, high resilience) and residents to be in a poverty trap (low potential, low connectedness, low resilience).

Food system indicators – potential

Data at the focal scale of the food system included food security rate and food security-related health outcomes as measures of potential, both of which link to household socio-economic status. Longitudinal data for food security were available, but not at the city scale; Feeding America (2020) publishes county, state, and national data annually. We found little publicly available, consistent, city-scale data. The "Map the Meal Gap" data set reports the food insecurity rate analyzed first at the state level, with coefficient estimates then applied to counties and congressional districts (Feeding America 2020). However, due to changes in methodology, the full longitudinal record was not comparable. For example, Fig. 4 shows the most recent prolonged period of food insecurity from 2009 to 2017, and indicates that post-Great Recession, food insecurity at the county scale was relatively stable in all three case studies, with a slight decline in Genesee County. All sites experienced a post-2008 increase in food insecurity as a result of the U.S. recession, which then began to decrease as the economy recovered (Ziliak 2021).

Fig. 4. Food insecurity rates at the county and state scale, 2009–2017 (Feeding America 2020). Genesee County, Michigan (MI) and Cuyahoga County, Ohio (OH) had similarly high and steady rates, which were higher than their state rate. Allegheny County, Pennsylvania (PA) reported lower food insecurity rates, which were similar to the Pennsylvania rate.



Also notable is that after 2012, food insecurity rates in Genesee and Allegheny Counties surpassed state levels, but Cuyahoga County always maintained a rate higher than the state level. This reflects lower potential within each county compared to their respective state. If food insecurity in all three counties was above their respective state average, we would anticipate above-average negative health outcomes (another inverse indicator of potential) because the literature has consistently found food insecurity to be negatively associated with health outcomes (Gundersen and Ziliak 2015). Some of the mechanisms by which food insecurity adversely affects health outcomes are indirect. For example, there is evidence that food insecurity is associated with obesity, which in turn is associated with other negative health outcomes, including diabetes, but it differs across genders (Larson and Story 2011). We found longitudinal data only for obesity at the state scale (Fig. 5) (United Health Foundation 2020) and diabetes at the county scale (Fig. 6) (CDC 2020). This poses a significant challenge to the cross-scale comparisons we attempted at the city scale; however, because this is a linked outcome of food insecurity, we present these available data.

Obesity rates increased over time relatively consistently among the three states (Fig. 5). There was some shorter time-series obesity data, for example, in Genesee County. The Genesee County obesity rate was consistently higher than the state and national averages, but after several years of trending downward (2008–2014), it began increasing (Greater Flint Health Coalition et al. 2019). However, county-scale data mask the city dynamics. At this scale, we found recent (2017) non-longitudinal data for obesity rates, which showed that among adults aged 18 years and over, the crude prevalence rate was 47.8% in Flint, 41.0% in Cleveland, and 29.7% in Pittsburgh

Fig. 5. Obesity rates as a proportion of the state population, 1990–2019 (United Health Foundation 2020), which is significant because obesity has been linked to food insecurity (Larson and Story 2011). Rates increased similarly across all three states, but longitudinal data were not available at the city scale. Data points for each city show Flint and Cleveland significantly above the state average.

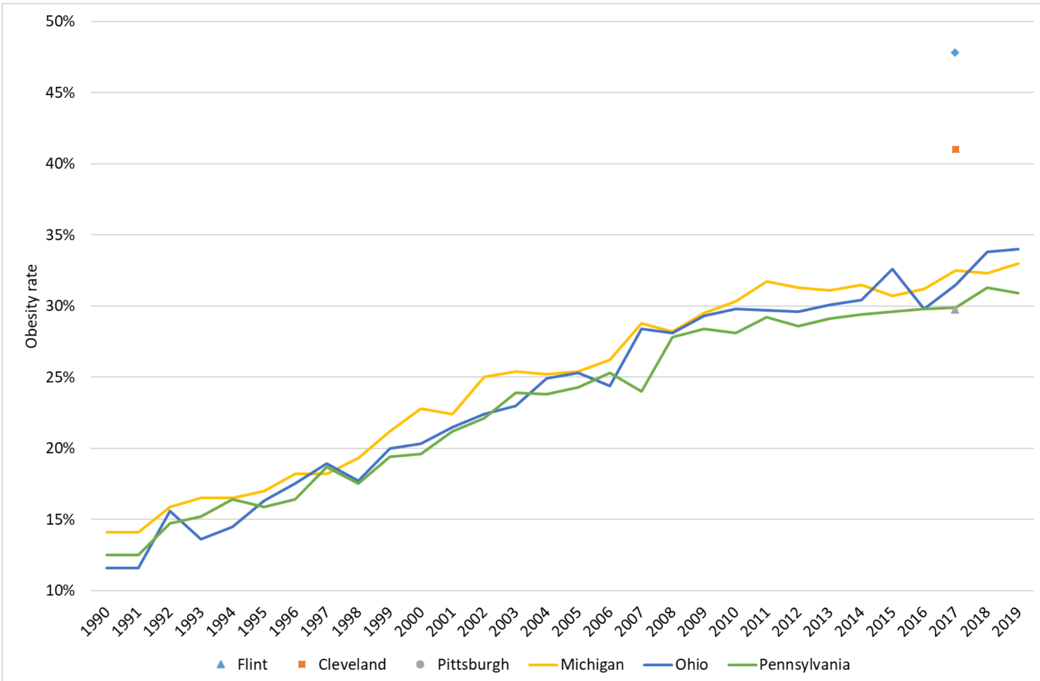
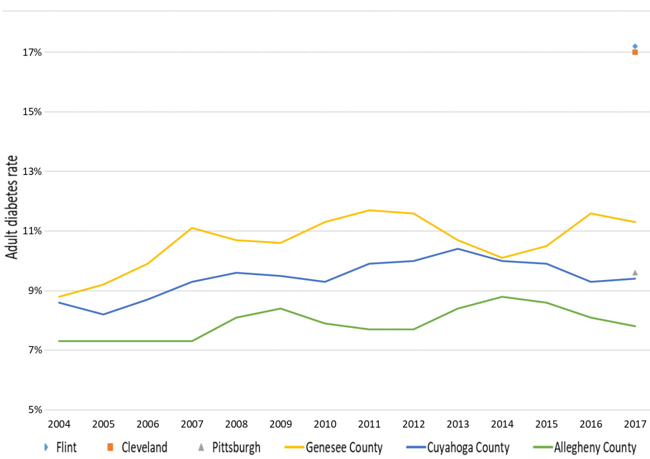


Fig. 6. Total percentage of adults (18+ years) with diagnosed diabetes, 2004–2017; longitudinal for county-scale data only (CDC 2020). Rates for Flint and Cleveland were significantly higher than the rates for their counties, but there was a lack of longitudinal city-scale data. It is likely that county-scale data mask city dynamics.

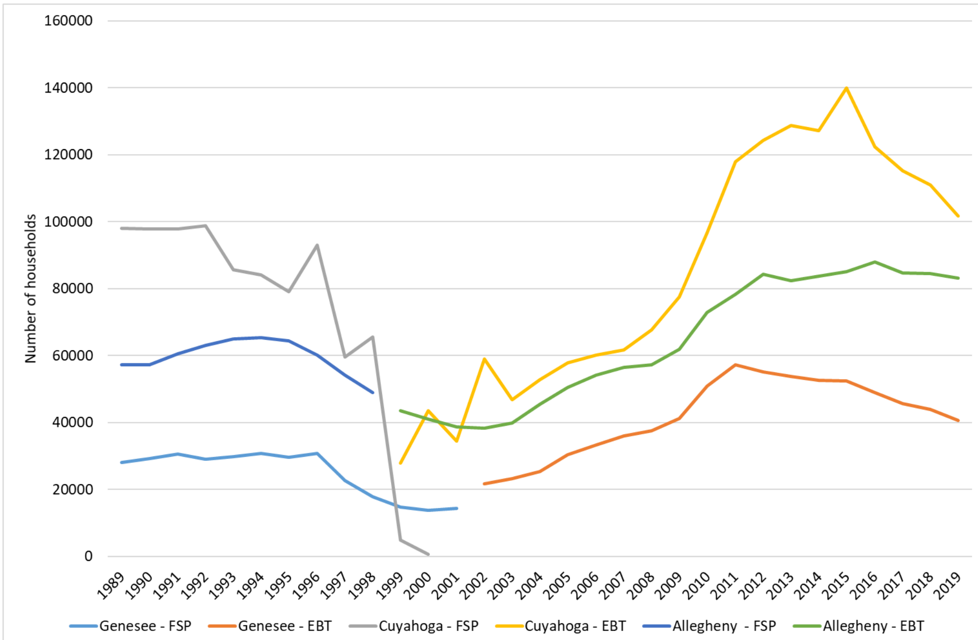


(CDC 2016). The Flint and Cleveland rates were substantially higher than their respective state average rates (Fig. 5), but Pittsburgh's rate was lower than the state average. With respect to diabetes, similar patterns were found at the county scale: Allegheny's rate was below that of Genesee and Cuyahoga (Fig. 6) (CDC 2020). The one-off city-scale data for diagnosed diabetes among adults aged 18 years and over showed that the rates in all cities were above those in their respective counties in 2016: Flint at 17.2%, Cleveland at 17.0%, and Pittsburgh at 9.6% (CDC 2016). Our interpretation is that health as a form of potential was therefore less available in Flint and Cleveland, but in Pittsburgh, the food system dynamics did not appear to negatively affect this form of potential.

Food system indicators – connectedness

Given that the food insecurity rate was higher in Cuyahoga County and thus presumably Cleveland compared to Genesee County, it is interesting that there were more negative health impacts associated with food insecurity in Flint. To explore this, we examined other food security indicators that represent connectedness; for example, participation in the Supplemental Nutrition Assistance Program (SNAP) as reported at the county scale by the United States Department of Agriculture Food and Nutrition Services (USDA FNS 2020). We interpreted this as connectedness rather than potential because the rate of participation refers to whether resources are flowing from state to household rather than the resource itself. Again, longitudinal data were interrupted by a change in methodology in the early 2000s, when the United States Department of Agriculture switched from the Food Stamp Program to Electronic Benefits Transfer, as demonstrated by the different data sets in Fig. 7 (USDA FNS 2020). Again, data were available only at the county scale; therefore, the specifics of the city-scale food system were unavailable. However, there were trends that helped contextualize the overarching city-scale analysis. Participation in SNAP is

Fig. 7. Total number of participating households in the Supplemental Nutrition Assistance Program, as both the Food Stamp Program (FSP) and Electronic Benefits Transfer (EBT), presented at the county scale, 1989–2019 (USDA FNS 2020). A change in methodology is reflected in the graph. Absolute numbers show that Cuyahoga County consistently had the highest participation and Genesee County had the lowest, but this also reflects the higher population of Cuyahoga (1,235,072 in 2019) and Allegheny (1,216,0450) compared to Genesee (405,813) (U.S. Census Bureau 2020c).

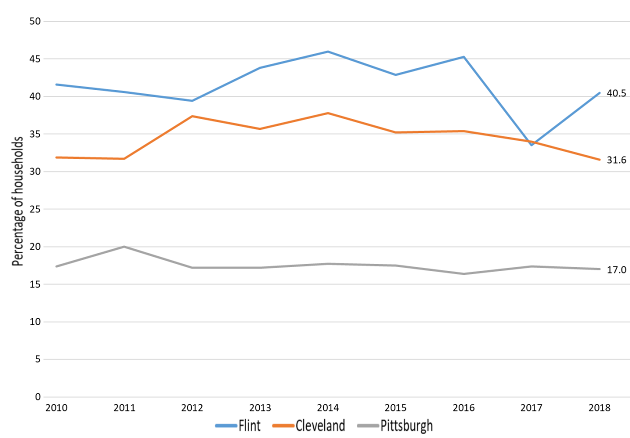


influenced by individual circumstance but also state policy and funding. The increase in SNAP enrollment following the Great Recession was associated with unemployment (Ganong and Liebman 2018). While unemployment eventually declined and the population continued to decrease, SNAP participation did not return to pre-recession levels for Allegheny or Genesee County (U.S. Bureau of Labor Statistics 2021a, b, c).

A decade of SNAP data at the city scale was available from the American Community Survey (Fig. 8) (U.S. Census Bureau 2020d). Adjusted for population, our interpretation is that city-scale data demonstrated that the county patterns were intensified. Similar to other indicators, city outcomes were worse than county indicators. Flint had the highest proportion of SNAP recipients at 40.5%, more than double that of Pittsburgh (17.0%). The SNAP data indicated that all three cities showed important flows of resources between food-insecure households and local government (again, an indication of low potential at the household scale that requires supplemental resources) and that such connectedness was greater in Flint.

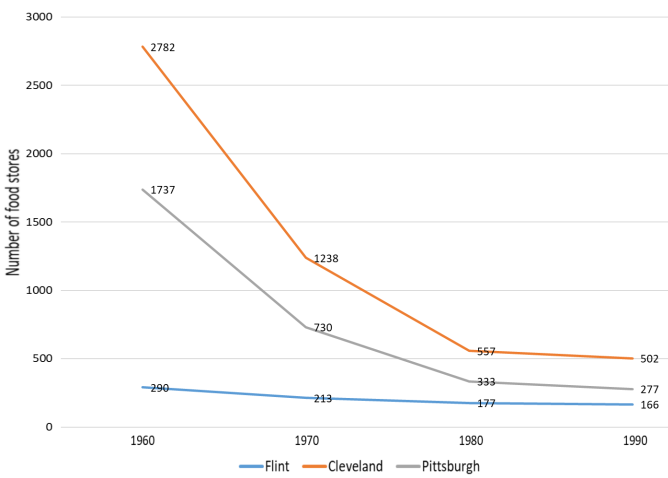
Another indicator of connectedness that provided data at the city scale was the number of food store establishments available in each city (of interest because they support access to food resources; i.e., a flow, rather than data on food resources themselves). City census data showed declines in the number of food stores (measured as establishments) from the 1960s onward,

Fig. 8. Percentage of total households that received food stamps or Supplemental Nutrition Assistance Program (SNAP) benefits, at the city scale, 2010–2018 (U.S. Census Bureau 2020d). These data were available only from 2010, unlike the county-scale data, which are presented over a longer period in Fig. 7. While Genesee County had the smallest absolute number of households that received SNAP benefits, Flint had the highest proportion of participants. Adjusted for population, city-scale data demonstrated that the county patterns were intensified, which illustrates a need for a distinction between city- and county-scale data.



which parallels nationwide trends in the decrease of "mom and pop" small-scale corner stores and an increase in larger supermarket chains and grocery stores (U.S. Census Bureau 2020a). Steep declines in the number of food store establishments occurred in Cleveland and Pittsburgh from 1960 to 1990 (which likely corresponded to decreases in the population as a whole in those areas); Flint showed a much steadier, although still declining, number of food establishments (Fig. 9). This is an important distinction because while Flint had more food establishments per capita, it had higher food insecurity rates than Cleveland and Pittsburgh.

Fig. 9. Total number of food store establishments in Flint, Cleveland, and Pittsburgh, 1960–1990 (U.S. Census Bureau 2020a). Flint had fewer establishments in 1960 but had retained 57% of them by 1990, whereas the number in Cleveland and Pittsburgh decreased by more than 80% over that period. Although Flint had more food store establishments per capita, it had higher food insecurity rates than Cleveland and Pittsburgh.



Beginning in 2002, the U.S. Census Bureau changed the ways food establishment data were collected to determine more specific metrics for the types of food stores by dividing grocery stores into two categories: supermarkets and convenience stores. In 2012, specialty food stores were added. As per the U.S. Census Bureau Classification Development Branch (U.S. Census Bureau CDB 2021), supermarkets are defined as "establishments generally known as supermarkets and grocery stores primarily engaged in retailing a general line of food, such as canned and frozen foods; fresh fruits and vegetables; and fresh and prepared meats, fish, and poultry. Included in this industry are delicatessen-type establishments primarily engaged in retailing a general line of food" (U.S. Census Bureau CDB 2021). Convenience stores are defined as "establishments…primarily engaged in retailing a limited line of convenience items that generally includes milk, bread, soft drinks, snacks, tobacco products, newspapers and magazines" (U.S. Census Bureau CDB 2021). The new category of specialty food store added in 2012 is defined as "permanent fruit and vegetable stands, specialty meat stores, etc." and would incorporate a newer trend for niche stores that focus on local products (U.S. Census Bureau CDB 2021). Like much of the census data, this poses challenges for researchers who attempt to draw comparisons across time. Nevertheless, from 2002 to 2017, there was a continual decline from the 20th century (Fig. 9) in the number of stores available for residents to access food in Flint, but the total number of establishments in Cleveland and Pittsburgh remained relatively static (Fig. 10) (U.S. Census Bureau 2020a). Both Flint and Cleveland experienced a decline in supermarkets, and all cities showed a decline in specialty stores, but in Cleveland and Pittsburgh, new establishments were added as convenience stores (Fig. 10).

Because there are significant population differences among the three cities, we compared the supermarket data per 10,000 people in the population to provide a more effective means of comparing food access among residents within the city. Fig. 11 shows the total number of food store establishments per 10,000 residents (1960–1990); Fig. 12 shows the number of supermarkets per 10,000 residents (2002–2017) (U.S. Census Bureau 2020a, b). For the number of supermarkets reported in 2002, 2012, and 2017, we used population data from 2000, 2010, and 2018, respectively (U.S. Census Bureau 2020b). While Cleveland and Pittsburgh had the greatest change in total number of establishments per 10,000 people, Flint had a higher density of food stores through the 20th century and maintained a comparatively high density of supermarkets into the next century, although with some decline. These analyses would benefit from more specific exploration and primary data collection, as other evidence shows that most major grocery stores in Flint are outside the city, having left in the 2010s, which has left some neighborhoods with limited sources of affordable, healthy food (Shaver et al. 2018). Considering all the grocery store data, we would interpret Flint as currently having higher levels of this form of connectedness, and that Cleveland and Pittsburgh have lost significant connectedness since the 1960s.

Adaptive cycle dynamics at the food system scale

The time series of data used to analyze the adaptive cycle dynamics at the food system scale was shorter than the time series of data that was available to analyze the adaptive cycle dynamics at the city-county scale, and there were relatively few data at the city scale, but indicators suggest that during the study period, the food system was in a different phase in Pittsburgh/Allegheny County than in Flint/Genesee County and Cleveland/Cuyahoga County. Food insecurity in Allegheny County was still above the national average but was lower than in the other two counties. There were also fewer negative health outcomes in Allegheny County than in Genesee and Cuyahoga Counties, which both demonstrated high food insecurity and high negative health outcomes, interpreted as low potential. Therefore, while the higher levels of SNAP issuance in Genesee and Cuyahoga Counties indicated higher levels of connectedness, we interpret this connectedness and the resulting resilience as coerced (Angeler et al. 2020), whereby external subsidy artificially maintains the regime and prevents it from collapse and reorganization. In Flint/Genesee County and Cleveland/Cuyahoga County, a low potential, high connectedness, and high (coerced) resilience (given the prolonged nature of these patterns) would indicate a lock-in trap. Lock-in traps are created when systems spin off from the release phase (Fig. 13) and cease to be adaptive given the erosion of potential and diversity, with the resulting impoverishment causing resilience to increase because the state is so depauperate that it stabilizes (Allison and Hobbs 2004). In contrast, the transition in Pittsburgh/Allegheny County resulted in higher levels of potential and connectedness, which indicates the system was in the fore-loop (exploitation to conservation, as shown in Fig. 13); additional data would allow us to clearly identify the phase.

Fig. 10. Number of food stores as three major types of establishments—supermarkets, convenience stores, and specialty food stores—outlined in the economic census, at the city scale, 2002–2017 (U.S. Census Bureau 2020a). While the number of supermarkets and convenience stores declined in Flint and Cleveland, limiting food access points for residents, they remained similar in Pittsburgh.

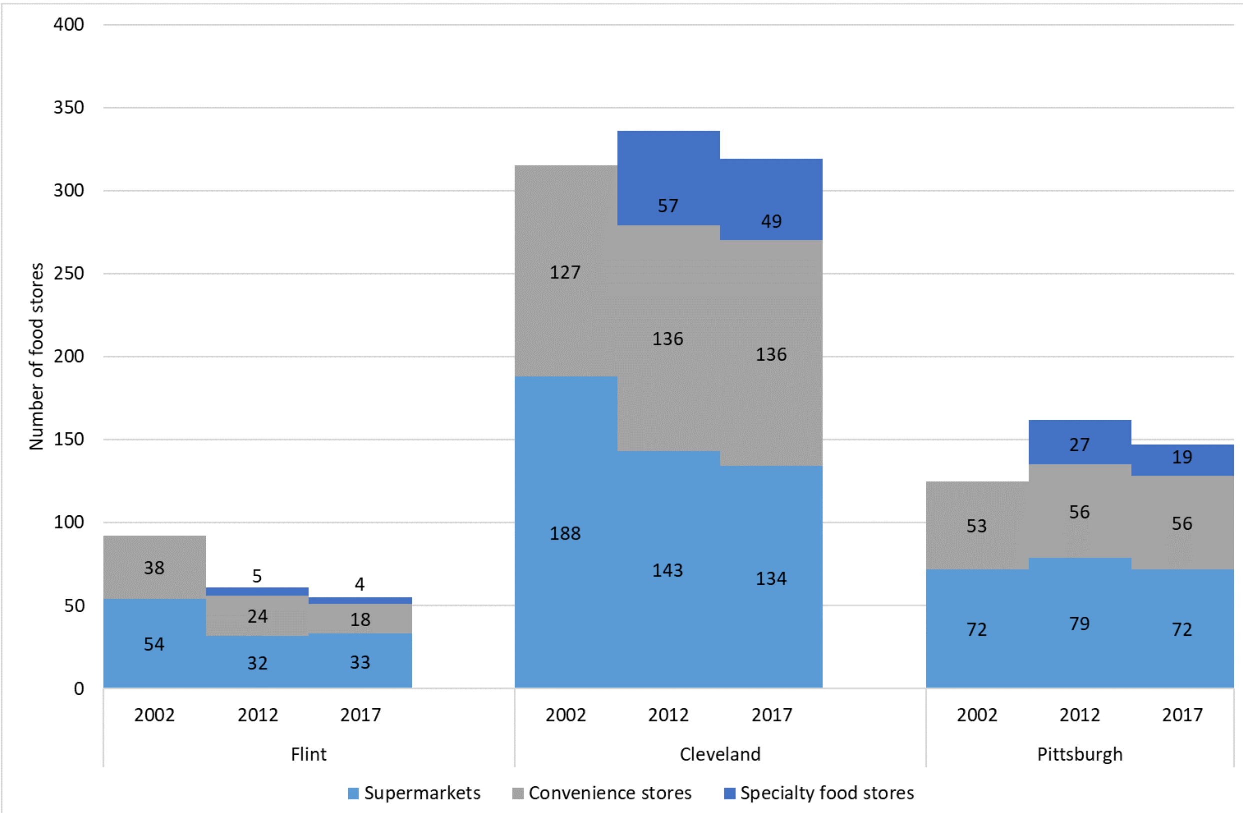


Fig. 11. Total number of food store establishments per 10,000 residents, at the city scale, 1960–1990 (U.S. Census Bureau 2020a, b). Flint, the smallest city, maintained a higher density of food establishments after the late 1970s than did Cleveland and Pittsburg; however, in context with other data, we know that due to closures in the 2010s, most of the major grocery stores in Flint are now outside the city limits.

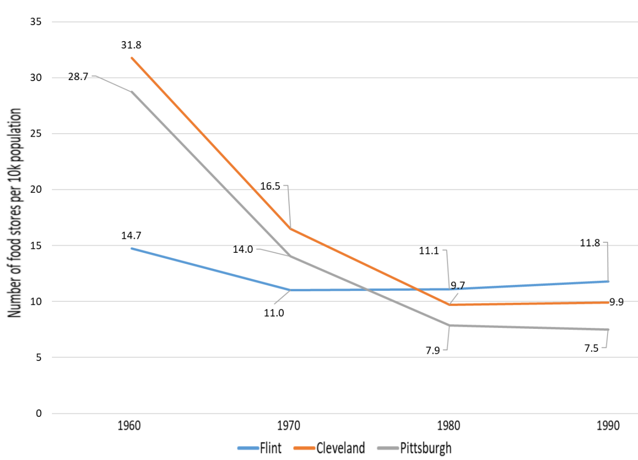


Fig. 12. Total number of supermarkets per 10,000 residents, at the city scale, 2002–2017 (U.S. Census Bureau 2020a, b). The number of supermarkets increased slightly in Pittsburgh during this period but decreased in Flint. The decrease in Cleveland was larger than the increase in Pittsburgh.

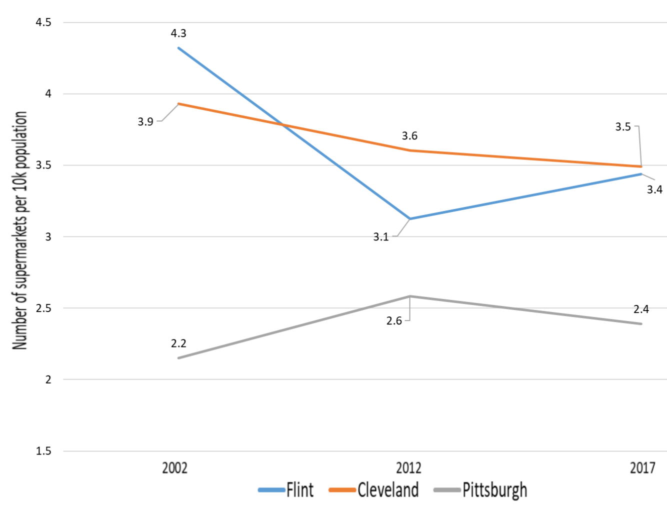
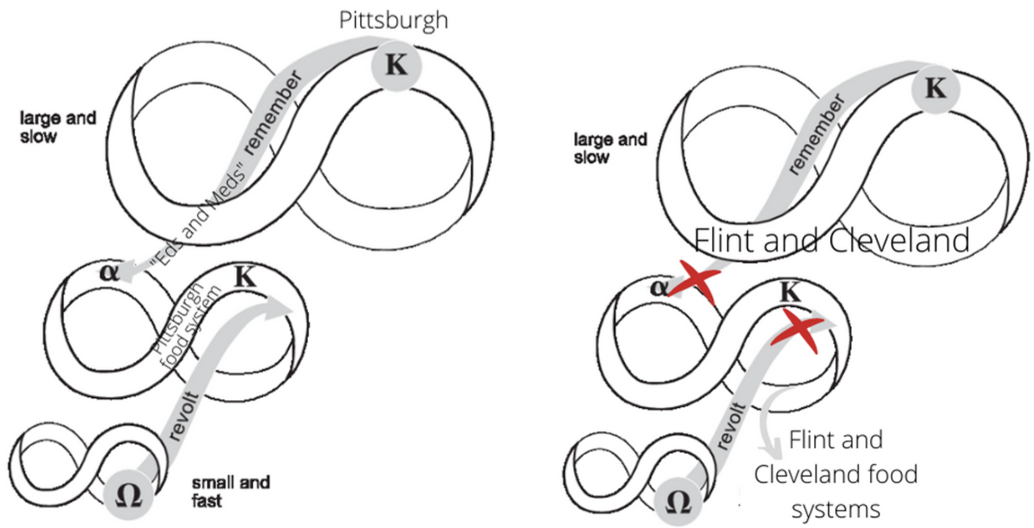


Fig. 13. Combining our analyses within a panarchy framing showed that Pittsburgh reorganized into a post-industrial conservation phase, which supported the release and reorganization of the food system through remember dynamics. In contrast, Flint and Cleveland were in phases of the adaptive cycle with low potential, and this was blocking revolt and remember dynamics, which led to their food systems being in a lock-in trap.



These dynamics were further validated by positioning the food system within the broader panarchical dynamics (Table 4). In Pittsburgh, the public–private partnerships appear to have supported reorganization of the city out of the deindustrialization regime into a new conservation regime characterized by the "eds and meds" economy, in which reinvestment focused on several university systems located within the city ("eds") and an expansive hospital system and medical insurance industry ("meds"), all with substantial impacts on the economy. The new system created remember connections (i.e., large and slow cross-scale connections where accumulated experience, knowledge-system integration, and visioning lead to change) in the food system, which resulted in its improved outcomes, as shown in Fig. 13 (Folke 2006).

In contrast, both Flint and Cleveland were characterized by low potential. While this could indicate exploitation, release, a poverty trap, or a lock-in trap (see Table 1), we suspect one of the traps, given the presence of coerced forms of resilience at the food system scale. The presence of traps blocks revolt and remember connections that were observed in the past during the peak of industrialization and which supported a thriving food system. In particular, a lock-in trap limits bottom-up innovation feeding up through revolt mechanisms. While innovation occurred in these cities—for example, there were many initiatives within Flint that aimed to increase residents' access to affordable fresh fruits and vegetables (Edible Flint, Flint FARMacy, Flint Fresh, the North Flint Healthy Food Initiative)—these initiatives did not scale to long-term measurable impact on city-wide food insecurity. Instead, the food system was dependent on federal support (SNAP) that bypasses the city's resources, coming from an even larger institutional scale.

Integrating the historical data for each city helped explain the food system dynamics. Flint is a Black-majority city in a white-majority county and has shown limited response to deindustrialization, indicated by continuing depopulation and high unemployment. In contrast, Pittsburgh reinvigorated its economy, which created more diverse employment and slowed depopulation. While its rate of food insecurity is still above the national rate, its median income has recovered, and there is more potential in the city and the food system, indicating that the food system will be more resilient to future change. Cleveland is somewhere in-between these two examples—while economic reinvention has begun, the benefits have been distributed unevenly, with racial segregation by neighborhood and pockets of persistent poverty. We cannot discount the effects of institutionalized racism in all these examples, which is a factor that differentiates investment in Flint (54.1% Black population) from that in Pittsburgh (22.9% Black population) (U.S. Census Bureau 2020b, Lynch et al. 2021).

DISCUSSION

There were multiple indicators identified that would ideally inform a comparative study but which are not available (Table 1). Thus, we were limited by data availability both in time (i.e., longitudinal records did not exist) and space (i.e., different indicators had data at different spatial scales but relatively little at the city scale). Such limitations may vary in different countries, but in the United States, we suspect differences in how data are collected and published at the city and county scale led to some patterns being muted in our analysis. Therefore, we end with two main implications for the operationalization of panarchy: (1) scale and place must be clearly differentiated in the data and understood to be able to inform panarchy analyses, and (2)

Table 4. Summary of relative levels (low to high) of potential and connectedness indicates the different cities are in different phases of the adaptive cycle.

	Adaptive cycle component	Indicator	Flint/Genesee	Cleveland/Cuyahoga	Pittsburgh/Allegheny
Household	Potential	Median income raw and adjusted 2020 dollars	Lower	Lower	Higher
		County average cost per meal	Lower	Higher	Higher
Food system	Potential	Food security rate (county, state; inverse)	Lower (county scale higher than state)	Lower (highest county scale, higher than state)	Lower (most similar to state average, although slightly higher)
		Health outcomes – obesity (state), diabetes (county; city in 2017)	Very low (high rates of diabetes and obesity compared with county and state)	Lower (high rates of diabetes and obesity compared with county and state)	Higher (similar to county and state)
	Connectedness	Supplemental Nutrition Assistance Program – county issuance, number of households as proportion of county	Higher – 40%	High – 32%	Average – 16%
		Grocery stores as proportion of the population	Higher	Medium	Lower
City	Potential	Population (race dynamics)	Increasing till 1960s, decrease, still low currently	Increasing till 1960s, decrease, still low currently	Increasing till 1960s, decrease, showing some increase but still low
		Poverty rate	Increasing till 1960s, decrease, still low currently	Increasing till 1960s, decrease, still low currently	Increasing till 1960s, decrease, showing some increase but still low

secondary data limitations will limit the potential to conduct comparative studies—studies of panarchy in food systems, and presumably other types of SESs; therefore, primary data and in-depth knowledge of the case study will be required to overcome such limitations.

Scale and place

Although limited by data availability, our analysis demonstrates that understanding particular spatial-temporal cross-scale dynamics is important to explain how each city's food system evolved to its current regime, given the nested nature of such complex systems. Therefore, county data alone should not be used to make conclusions for the city, and our analysis potentially obscures important distinctions between cities and counties. Of particular note is the representative population density of each city within the county—Pittsburgh is 3.26 times as dense as Allegheny County as a whole, and Cleveland is 1.82 times as dense as Cuyahoga County as a whole (U.S. Census Bureau 2020c). However, Cleveland makes up a bigger physical part of the county (78 of 457 square miles [202 of 1184 square kilometers]) than do the other cities, which may partially explain why Cuyahoga County is so densely populated. In contrast, Flint is 4.49 times as dense as Genesee County (U.S. Census Bureau 2020c), which suggests that Cleveland and Cuyahoga County are most alike in terms of population density, and Flint and Genesee County are least alike. This is important when comparing county-scale data to city-scale data—their respective county-scale data will represent Cleveland and Pittsburgh better than Flint. Thus, the food system analysis for Flint is likely an underrepresentation of the potential within the food system. Similarly, there are important racial distinctions between city and county data that can also mask differences when comparing city and county data. For example, Flint's population is 54.1% Black, while Genesee County's is only 19.9% Black; Cleveland's population is 47.4% Black, while Cuyahoga County's is 29.2% Black; and Pittsburgh's population is 22.9% Black, while Allegheny County's is 12.9% Black (U.S. Census Bureau 2020b). Flint is the only Black-majority city in this study, followed closely by Cleveland, yet none of the counties are Black majority. The City of Flint and Genesee County represent the biggest distinction in racial data when comparing these cities and counties. We see this in our in-depth work in Flint, where primary data collection has allowed us to supplement the indicators listed here and create a more detailed understanding of the cross-scale dynamics, particularly in how structural racism and urban poverty influence food security (Hodbod and Wentworth 2022). Due to a lack of city-scale data, we should be extremely careful about the context in which we make cross-scale comparisons because county-scale data hide city-scale patterns. Without this knowledge, there could be hidden variables that confound comparisons, such as vast racial differences between city and county, and size of city versus county, which means comparisons in some areas do not apply to others. This is particularly significant in areas where the size of the Black population is much larger in the city than in the county due to persistent effects of structural racism (Lynch et al. 2021).

Data limitations

We have hinted at two elements of data limitation: (1) secondary data are limited at smaller focal scales (i.e., food systems at the city scale and below), and (2) analyses are limited by just secondary data; primary data are necessary to fill the gaps, and qualitative data are essential to provide context. Both limitations influence how we operationalize panarchy. The complexity of SESs means there are many indicators that can be used to understand potential, connectedness, and resilience, so researchers have to make decisions about which indicators to use and have to be clear in their justification. But the limitations of secondary data sets may reduce the potential for comparative panarchy analyses, which explains why the current literature commonly uses panarchy in one focal SES over time (Fraser 2003, Allison and Hobbs 2004, McAllister et al. 2006, Fraser 2007, Dugmore et al. 2009, Moen and Keskitalo 2010, Rosen and Rivera-Collazo 2012, Perez Rodriguez and Anderson 2013, Stroink and Nelson 2013, Salvia and Quaranta 2015, Rawluk and Curtis 2016, Teuber et al. 2017, Jiménez et al. 2020). These studies commonly integrate mixed methods approaches, synthesizing primary data collection with historical narratives, which is easier at a smaller scale than mid-size cities, as we attempted here. While mixed methods approaches require additional resources, we argue that they are essential to panarchy analyses of food systems, especially where data are not publicly available for food system studies.

Longitudinal food system data at more granular spatial-temporal scales would address both the limitations we have outlined. Our analyses, while limited, support the rationale for using history to understand food systems and for recognizing distinctions between place (i.e., county and city) which otherwise can significantly hinder our understanding of cross-scale interactions. Food system research needs to move beyond county and national scale data and acknowledge diversity within our food systems, in both the global north and south. In the United States, strengthening analyses requires more city-scale data, which could be achieved by adding food-system questions to the American Community Survey and similar statewide studies. More generally, assessing resilience or panarchy (common approaches to and metrics of, which have been recently called for [Angeler et al. 2015, Knippenberg et al. 2019, Jones et al. 2021]) requires common data across multiple spatial-temporal scales to support an understanding of the local context.

CONCLUSION

We have outlined the first comparative study of three urban food systems, using a panarchy framing to explore how social and economic history influenced the food system in three case studies in the U.S. Rust Belt. Economic recovery at the city scale in Pittsburgh, Pennsylvania was reflected in reorganization in the food system, while the lack of economic recovery in Flint, Michigan and the uneven access to economic recovery in Cleveland, Ohio potentially placed both cities and food systems in lock-in traps. However, we cannot make these conclusions definitively because key data were missing, both at the city scale and over time. Overlooking such gaps may lead to making assumptions about cities based on county data, which might not be accurate or may hide critical variables such as race or geographic size, and which anecdotal and primary data may contradict. Therefore, we end on a note of caution: be clear about scale in panarchy analyses and acknowledge the limitations of current data sets.

However, even though our analyses were limited, we still advocate for operationalizing panarchy to understand food systems. Panarchy allows for the identification of important indicators of potential, connectedness, and resilience at multiple scales of interest. Critically, it supports the incorporation of place and historical context into analyses, which can lend valuable explanatory power. Such analyses also show when we are not collecting the right data to make comparisons that further our understanding of urban food systems. This acknowledgement provides a crucial check on our assumptions and reveals the importance of incorporating the impacts of structural racism in our analyses. Addressing these limitations will ground our understanding of food systems in a social-ecological context and will simultaneously help develop panarchy theory.

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[1] We used 1 June 2020 as the standard date to calculate all 2020 U.S. dollar amounts adjusted for inflation.

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Data Availability:

The data that support the findings of this study are from resources available in the public domain.

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