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Sustainability and resilience through connection: the economic metacommunities of the Western USA

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ABSTRACT. Regional social, environmental, and economic systems form a rich web of connections that both create opportunities and pose risks. Regional economies, characterized by their interconnectedness across jurisdictional boundaries, might be better managed at a transboundary scale because they can leverage a broad resource pool and greater economic diversity compared to a single jurisdiction alone. The technical challenge is to identify which economies are connected and could be managed collectively to better mitigate, absorb, and recover from disruptions. Economic risk management often occurs at the state level, but network approaches can identify groups that interact with one another based on actual commodity flows, capturing important features of the system that are not currently coordinated. One such approach, based on ecological theory, is to identify economic metacommunities. We use theories and methods from metacommunity ecology to identify overarching structures in the Western U.S. trade network. Specifically, we construct commodity flow networks for 25 metro and rural areas, then assess these using the ecological concepts of interaction strength, diversity, clusters, and sources and sinks to identify five economic metacommunities. Based on metacommunity membership, we answer the question: Which regions in the Western USA are interdependent, and are interdependent regions spatially proximate or not? These results are useful in economic development and infrastructure planning for developing redundancy, targeting vulnerable interdependencies, and understanding potential risks from adverse policy exposure.

Key Words: *metacommunities; network modularity; regional economies; trade networks*

INTRODUCTION

Sustainability and resilience are essential concepts that shape the long-term economic development, stability, and security of regional economies. Regional sustainability can be defined as the ability of a regional economy to sustain the current socioeconomic and environmental conditions while maintaining possibilities for long-term development (Smetana et al. 2015). Achieving sustainability ensures that regional economies can continue to exist without depleting ecosystem services and natural resources and compromising the ability of future generations to meet their own needs (WCED 1987). Regional economic resilience (RER) is the ability of regional economies to resist disruptions or recover from them to achieve pre-disruption economic performance, either by adapting or transforming themselves (Sutton et al. 2023). Greater RER indicates that economies are less likely to have their long-term growth trajectories drastically altered (Fingleton et al. 2012, Sutton and Arku 2022).

Although this study does not directly examine the resilience or sustainability of regional economies, it introduces a novel theoretical framework to assess the structure of trade relationships, which underlies both economic resilience and economic sustainability (Kharrazi et al. 2017). Trade connections lead to greater diversification of resources and potential supplies, but also make a region vulnerable to disruptions from those suppliers; some economic network structures have been shown to be more resilient than others (Gomez et al. 2021). Multiple transboundary factors affect RER, including infrastructure such as transportation routes alongside trade relationships or agreements both domestically and internationally (North 1955, Lemke et al. 2023, Sutton et al. 2023). As a region's limited natural resources are increasingly shared across borders, understanding how system-level stressors, such as natural and human-made disasters, can lead to overdependence and overconsumption of resources is vital because these factors can negatively impact the sustainability of regional economies (Kharrazi et al. 2013, Gephart et al. 2016).

Existing literature highlights the need for system-based approaches to understand the dynamic interactions between agents in complex regional economies (Tamayo and Vargas 2019, Sutton and Arku 2022). By investigating the structure of interregional trade flows and relationships, we can identify clusters or “communities” of regions closely linked through trade, sharing dependencies that shape their collective economic resilience and sustainability. This approach can help resolve questions around the conceptualization and determinants of RER by identifying factors that impact resilience, including interdependencies within regional economic networks and the impact of past behavior on trade network evolution (Simmie and Martin 2010, Evenhuis and Dawley 2017, Cainelli et al. 2019). RER literature has often viewed regions as fixed, self-contained spatial units defined by predefined administrative boundaries and available geo-location data. This conventional RER approach does not account for complex socio-spatial relations and their influence on regional economies (Lemke et al. 2023). To address this methodological gap, this study introduces an adapted metacommunity ecology approach, which applies principles from ecology to analyze regional economic interactions within the broader Western U.S. (WUSA) trade network (Martin et al. 2016, Evenhuis and Dawley 2017, Feng et al. 2023). Metacommunity ecology studies groups of interacting communities across different spatial scales, focusing on how species move, interact, and adapt across regions (Mouquet and Loreau 2003, Leibold et al. 2004). By incorporating complex multi-scalar spatial interactions of regional economies, this study provides insights into how the inter-regional interconnections and interdependencies can shape RER and regional sustainability (Bristow and Healy 2020, Lemke et al. 2023). This study aims to identify the emergent economic metacommunities of the WUSA and the structural interdependencies of their trade networks.

Prior studies across a broad range of research domains have made efforts to investigate the complex networks that constitute

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regional economies and the diversity of their interactions. These studies have covered topics such as water availability networks (Rushforth and Ruddell 2018, Garcia and Meija 2019), food supply networks (Lin et al. 2019, Davis et al. 2021, Gomez et al. 2021), carbon emissions (de Chalendar et al. 2019, Moiz 2022), energy footprints (Liu and Kontou 2022, Raimi et al. 2022), and environmental footprints (Lant et al. 2023, Paudel et al. 2023). Although these studies occasionally identified interacting regions within networks, they did not quantitatively interrogate community interdependence or how it has evolved over time, an aspect central to the adapted metacommunity approach, which captures the interdependence between regions.

Other studies have focused on identifying community structure but have not leveraged economic networks. For example, prior studies identified “megaregions” in the U.S. based on the clusters of dense populations and economically integrated areas, proposing these as the appropriate scale for metropolitan infrastructure planning (Gottmann 1957, Hagler 2009, Filipovitch 2023). U.S. megaregions have been identified several ways, e.g., by weighting regional characteristics (Hagler 2009), commuting flow estimates with network science algorithms (Nelson and Rae 2016, Zhang and Lan 2022), earth observation tracking of urban sprawl patterns (Taubenböck and Wiesner 2015), and the clustering of employment statistics (He et al. 2020). Megaregions are one step toward identifying the collective but uncoordinated factors that have long been acknowledged to influence sustainability and resilience in the RER literature (Lemke et al. 2023, Sutton et al. 2023). However, unlike megaregions, which have been defined by geographic or economic integration at large scales, the metacommunity approach focuses on the interdependencies between regions, emphasizing the spatial interactions that drive resilience and adaptation across multiple spatial scales.

Linking ecologic and economic systems

By applying a social-ecological network lens, we can analyze regional economic trade networks as complex systems (Holland 1992). This approach allows us to draw biomimetic analogies between economic and ecological network solutions for WUSA trade network organization, resilience, and sustainability (Gruner and Power 2017, Helmrich et al. 2020). Industrial ecologists have long been making these connections, framing trade networks as ecological systems focused on the flow of materials, energy, sustainability, and information (Graedel 1996, Erkman 1997, Pickett et al. 2001). A key advantage of this approach is that we can apply the same mathematical models used to study interactions and dynamics in ecological systems to economic systems, leading to unique economic insights. For example, ecology theory and methods have provided insights into how supply chains evolve (Simmie and Martin 2010), how diversity impacts trade networks resilience (Gomez et al. 2021), and how to manage trade networks for sustainability and resilience (Kharrazi et al. 2013, Gruner and Power 2017, Helmrich et al. 2020). These promising avenues demonstrate the potential for using metacommunity models and theory to better understand the structure and resilience of regional economies, offering a proof of concept for this study.

To explore parallels and extend concepts between regional economic trade networks and ecological systems, it is important

first to understand how natural ecosystems function as complex, interconnected networks. Ecosystems are complex systems that consist of interacting biotic organisms and their abiotic environments, which regulate population dynamics, species interactions, and resource availability (Chapin et al. 2002). Key ecological mechanisms such as predation, competition, reproduction, and mortality act as either positive or negative feedback loops that determine species' populations and habitat community compositions (Barabás et al. 2017). For example, high mortality rates can cause a positive feedback loop, where increasing deaths weaken the population and lead to further mortality. However, in a negative feedback loop, high mortality reduces competition for resources, improving the survival chances of the remaining population and stabilizing numbers. Biodiversity and structural connectivity are important aspects that maintain ecosystem stability and resilience, as diverse ecosystems possess greater redundancy and adaptability in response to disturbances (Walker et al. 1999, Wagg et al. 2022). A high level of biodiversity enhances the ability of ecosystems to absorb potential disruption impacts. At the same time, strong structural connectivity between habitats ensures the flow of species and resources, promoting recovery and long-term sustainability.

Community ecology, a sub-discipline of ecology, focuses on the interactions between species within a specific area and how these interactions shape ecosystem community structure and functions (Mittelbach and McGill 2019). Metacommunity ecology is an expansion of community ecology that studies groups of interacting communities across spatially heterogeneous landscapes, focusing on how species disperse, interact, and adapt across regions (Mouquet and Loreau 2003, Leibold et al. 2004). Both these theoretical and methodological frameworks allow for the investigation of the structure and dynamics of communities within ecosystems, providing insights into spatial distribution, resource flow, and resilience (Mittelbach and McGill 2019).

Several metacommunity concepts apply to studying regional economic structure and relationships. The “mass effect” in ecology describes how species that struggle to survive in one area can still maintain thriving populations in that area through continual immigration from more favorable “source areas” within a metacommunity (Shmida and Wilson 1985, Leibold et al. 2004). By analogy, in trade networks, strong production and business activity in one area of the metacommunity (sources) can support the economies of less active areas within the metacommunity (sinks) via trade. “Source-sink dynamics” describe areas where species thrive, reproduce, and generate excess populations (source), which then disperse to and support populations in less favorable areas (sink; Holt 1985, Pulliam 1988, Leibold et al. 2004). In trade networks, this equates to regions with excess production (source) supplying goods to areas with production deficits (sink), demonstrating a similar interdependence and specialization among regions. Although both the “mass effect” and “source-sink dynamics” represent the movement of individuals or goods from more favorable to less favorable areas, the key difference lies in their mechanisms: the “mass effect” emphasizes continuous dispersal that allows struggling populations or regions to persist through steady support, whereas “source-sink dynamics” focus on the surplus production in source areas that specifically sustains less viable sink areas over time. Finally, “species sorting” highlights how resource gradients affect

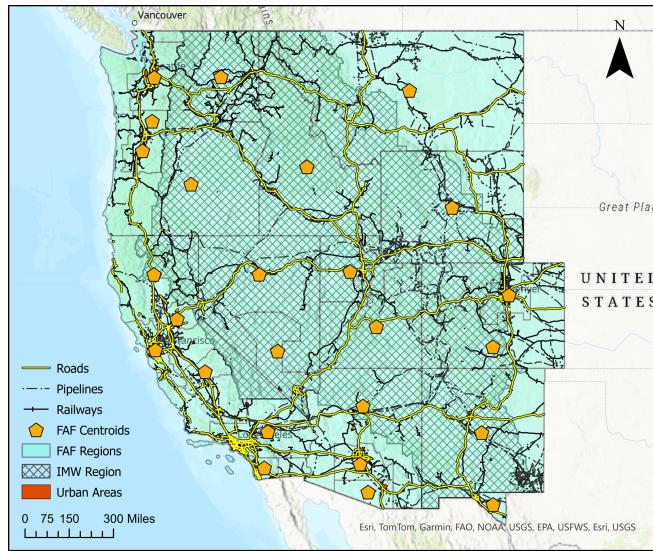
species' demographics and interactions within patches, emphasizing the role of dispersal in adapting to environmental changes (Leibold et al. 2004). For trade networks, the resource gradient represents the varying economic conditions across regions, where the movement of goods or people is crucial for balancing these differences. Goods disperse across this gradient to align resource availability with market demand, while people, such as workers with specialized skills, may move to regions where their expertise is needed. These concepts provide a foundation for analyzing how economic metacommunities interact and how commodities disperse across the trade network, with the ultimate goal of illuminating how these patterns impact RER (Heino et al. 2015, Leibold and Chase 2018).

In our formulation of the WUSA economic network, distinct commodities correspond to a “species,” and local economic activities correspond to “local community effects.” In community ecology, “local community effects” refers to how species interactions, population dynamics, and environmental conditions at a small, localized scale impact regional or landscape-level community structure and function. In terms of economies, these local economic activities are influenced by and exert influence on broader-scale economic processes. A key feature of these nested scales in ecosystems is their diversity, which provides latent adaptive capacity in the face of disturbance (MacArthur 1955, Holling 1973, Moore 1993, Legenvre et al. 2022, Wieland et al. 2023). Engineering diversity across scales can also be useful for trade networks (Turken et al. 2020), but previous studies do not address this multi-scalar component. Metacommunity ecology provides a novel, multi-scalar, and integrative approach to understanding complicated, heterogeneous economic connections and interdependencies in regional economies.

The WUSA region comprises the U.S. States of Arizona, California, Colorado, Idaho, Nevada, New Mexico, Montana, Oregon, Texas, Utah, Washington, and Wyoming (see Fig. 1). Because of its mountainous and semiarid desert terrain and historic economic specialization in mining and irrigated agriculture, it is characterized by large urban centers separated by vast, lightly populated, and semiarid expanses. Freight corridors are the main infrastructural and economic linkages between urban-rural, urban-urban, and rural-rural trading pairs (Wilmsmeier et al. 2011). Cities and towns in the WUSA are impacted by the accessibility and capacity of these freight corridors and other critical infrastructure (Simonson 2023). Even minimal disruptions to freight corridors can render some isolated communities vulnerable to social impacts, especially if the disruption occurs at points that link the WUSA region to the global economy, such as seaports and transborder crossings with Mexico and Canada (Cedillo-Campos et al. 2014, Verschuur et al. 2022). This sensitivity to trade connectivity across spatial scales creates an imperative to identify and understand the regional economic community structure and interactions and makes the WUSA an ideal case study (Doğan et al. 2023).

Using a metacommunity approach, this study answers the question: Which regions in the WUSA are interdependent, and are interdependent regions spatially proximate or not? We break this main research question into two distinct components. First, how do commodity flows organize the metacommunity structure and membership? Second, what are commodities' source and sink

Fig. 1. The 25 Western USA Freight Analysis Framework (FAF) regions (turquoise polygons) and geographical centroids (orange pentagons), along with the boundary of this region (gray gridded region), urban areas (red regions), railways (black continuous line with intermittent dashes), pipelines (dashed gray lines), and roads (yellow continuous lines). IMW = Intermountain West.



effects within metacommunities? In answering these questions, we provide a proof of concept for a method that will be useful for identifying multi-scalar structures within trade networks to improve coordinated planning for infrastructure and business investment, sustainability, and RER.

METHODS

Commodity flow data

This study uses the Freight Analysis Framework (FAF) version 5.5.1 to construct the trade network of 42 unique commodities in the WUSA region. FAF is a trade flow dataset produced by the U.S. Bureau of Transportation Statistics and the Federal Highway Administration, which combines several distinct federal trade and transportation datasets (Hwang et al. 2021). Version 5 constitutes observed and modeled data for 2017 and modeled trade flow volumes and values from 2018 to 2022. This study uses the observed 2017 trade flow volumes as a temporal snapshot to apply the model, in addition to not including potential inaccuracies from the modeled trade flows of 2018 to 2022. FAF covers the contiguous U.S., but this study focuses on the states that are either entirely in or partially in the WUSA: Arizona, California, Colorado, Idaho, Nevada, New Mexico, Montana, Oregon, Texas, Utah, Washington, and Wyoming (Fig. 1). The WUSA is divided by FAF into 25 local areas: 14 metropolitan areas, 7 rural remainders of a state, and 4 largely rural states. Figure 1 displays the Western States of the U.S. divided into 25 FAF regions, each with a geographical centroid corresponding to a “local” economic area within the region. The Intermountain West (IMW) subregion is denoted in hatched lines along urban areas and critical infrastructure such as railway, pipeline, and road

networks; this inland and largely rural subregion depends on west coast ports including the large ports of Seattle, WA, Portland, OR, San Francisco, CA, Los Angeles, CA, and San Diego, CA for access to the global economy, in addition to land borders with Canada and Mexico and transcontinental land routes to the Eastern U.S. via Denver, CO, El Paso, NM, and Albuquerque, NM.

Adapting metacommunity methods to economic networks

To delineate an economic metacommunity according to our chosen method (below), we must first define the metacommunities within the WUSA trade network. One common network science method used to do this is community detection based on network modularity. Network modularity is defined as a function of the total number of connections within a network set that lie entirely within a proposed community boundary rather than across community boundaries (Newman and Girvan 2004). This modularity metric tests intra-community connections against random alignments of communities, with values of 0 indicating the allocations of nodes into communities as “no better than random” and with values of 1 inferring “networks of strong community structure” (Newman 2006). By treating the FAF dataset as a network that consists of nodes (FAF regions) and edges (imports and exports of commodities) we can apply the Louvain community detection algorithm, which uses network modularity (Blondel et al. 2008).

The Louvain community detection algorithm is a robust method used to identify communities within larger networks by optimizing the modularity value (Blondel et al. 2008). The algorithm first assigns each node in the network (in this study, each FAF region in the WUSA trade network) to its own community. Then it iteratively merges communities by moving nodes between them to maximize the number of connections within a community while minimizing the connections between different communities. This step allows the algorithm to find the clusters of FAF regions that are more interconnected through their commodity flows, creating a network structure of economically independent regions. The Louvain algorithm is effective for analyzing large networks because it is computationally efficient and capable of revealing communities without the need for predefined spatial or geographic assumptions, making it well-suited to investigate trade networks across spatial scales (Blondel et al. 2008). The network community and modularity mathematical equations, expressed using adjacency matrices, are comprehensively presented in Zhang and Lan (2022). We have chosen not to reproduce them here to avoid redundancy and to maintain the focus on the application of these methods. The code and data used to run the Louvain algorithms is located in the GitHub repository provided in the data availability statement.

This study uses the Louvian community detection algorithm with a modularity value of 1 to identify emergent economic metacommunities based on the strength and frequency of trade flows to discern distinct trade communities within the WUSA trade network. The modularity value of 1 ensures that the identified metacommunities are strong, distinct communities based on their commodity flows that are not random in structure (Newman 2006). This method aligns with the mass effect and

source-sink dynamics metacommunity principles by examining how external flows can influence local populations. Defining trade network communities in this manner does not assume that communities are spatially linked or neighboring (as is often assumed in ecosystems). Previous studies show that trade relationships (and the resource use displacement they generate) do not always follow expected spatial patterns (Garcia et al. 2020). Grouping regional economies based on the flow of commodities highlights the economic dependencies and synergies that may not be apparent by just considering geographic distance. This approach reflects the realities of the global economy, where the impacts of market dynamics, economic policies, industrial characteristics, labor, and migration often transcend the barrier of geographic distance (Brei and von Peter 2018, Boulatoff et al. 2022).

Metacommunity source-sink model

In this study, we introduce a novel approach by applying the metapopulation concept, as initially proposed by Levins (1969), to analyze trade networks within the WUSA. In this model, the WUSA serves as the regional ecosystem in 2017, with each FAF region representing a community where multiple commodities (i.e., species) reside. The rationale for treating commodities as species in this model is their interregional flows and interactions with local economic conditions, influenced by production, consumption, and trade dynamics. This analogy allows the model to explore how commodities move through interconnected regions, similar to species distribution patterns across regional ecosystems, thereby enabling a deeper understanding of trade networks and economic interdependencies. As the first application of this adapted method, we sum all the commodity flows into a “total commodities” value for model simplicity. However, this model framework can distinguish individual commodities’ source and sink regions. Because the commodities flow through multiple local regions (communities), this mirrors the ecological dynamics of species distribution and interaction within metapopulations, offering a novel perspective to understand the complex interdependencies and flows within regional trade networks.

In adapting ecological models to industrial and economic systems, we must acknowledge several gaps. First, not all commodities possess ecological niches as species do; however, exceptions such as extractive sectors like mining, or the primary sector of the economy, tend to be geographically constrained (Kenessey 1987). Commodities such as water and energy that are spatially abundant are unlike species with precise reproductive rates and habitats in traditional ecology. Additionally, trade networks’ temporal and spatial boundaries, driven by market demands, production lead times, infrastructure limitations, and policies, differ substantially from ecological systems’ natural cycles and migration patterns. These differences underscore the complexities of applying ecological models to industrial and economic systems. Therefore, it is important to carefully consider the unique characteristics of commodities and human-driven factors when adapting ecological frameworks to these contexts. However, despite its simplicity, this model demonstrates that such adaptations are feasible and can offer insights into the dynamics of trade networks and economic interdependencies, showing potential for more refined future applications.

To detect source and sink regions of commodities in the WUSA, we adopt the source-sink metacommunity model by Mouquet and Loreau (Equation 2; 2003) that is composed of three hierarchical levels: local, regional, and metacommunity. Here, our hierarchical levels correspond to (first) the 25 FAF areas and (second) the several emergent economic metacommunities as identified by the Louvian community detection algorithm.

$$\frac{\delta P_{ik}}{\delta t} = [\theta I_{ik} + (1 - \alpha)c_{ik}P_{ik}]V_{ik} - m_{ik}P_{ik} \quad (1)$$

At the local level P_{ik} is defined as the proportion of sites occupied by species i in community k . Each species i is represented by a potential reproductive rate, c_{ik} , mortality rate, m_{ik} , and an explicit immigration function, I_{ik} . For each community, there are S species competing for a limited proportion of vacant habitat, V_{ik} . α measures the relative importance of regional and local influences in local communities, as well as the degree of coupling between population dynamics within the metacommunity. Dispersal success (θ) is the measure of an organism's ability to successfully find a new community, a key concept in metacommunity studies. Specifically, θ measures the dispersal success of immigrating species I_{ik} to vacant site k (Mouquet and Loreau 2003). Measuring species dispersal success is often challenging because of difficulties in tracking individual movements, leading to its usual indirect estimation or assumption in ecological research (Jacobson and Peres-Neto 2010). In a trade network context, we can observe the potential disruption to imports I_{ik} . This allows the model to incorporate scenario testing of dispersal failure and analyze how disruptions would impact economic metacommunities' structure. For simplicity, we assume that imports arrived with 100% success and removed θ from the equation. In addition to this simplification, we summed imports and exports respectively across commodities, resulting in a single import and export value (in tons) for each FAF region represented as the single species i in this model. Though we opted for methodological convenience for this proof of concept, future work should treat each commodity as a unique species i in the model to determine commodity-specific dynamics. We further modified the equation to better fit the context of regional trade networks by rearranging several terms:

$$\frac{\delta P_{ik}}{\delta t} = \frac{[I_{ik} - E_{ik}]}{V_{ik}} + [(1 - \alpha_i)c_{ik} - m_{ik}]P_{ik} \quad (2)$$

At the level of a FAF area, P_{ik} represents the tonnage of commodity i present in the context of the larger metacommunity community k as identified by the Louvian community detection algorithm. The total commodity tonnage i in k is characterized by self-supply flows of c_{ik} , consumption rate m_{ik} (calculated in Equation 4), observed import and export volumes I_{ik} , and E_{ik} . E_{ik} is not present in Equation 1 because emigrants were combined into a regional pool of dispersers and then equally redistributed to all other communities but is required to represent exports of commodity i from community k in Equation 2; this effectively adds a species emigration parameter to the original model in place of the equal redistribution of emigrants (Mouquet and Loreau 2003). We assume storage capacity corresponds to habitat patch availability in Equation 1 and so denote storage capacity as V_k .

However, the FAF database does not include information on storage/stocks. As a workaround, we assume that V_k is 1 to normalize this parameter across all FAF regions. Future work with more refined storage data could improve this procedure.

At the level of local communities (FAF regions), we need another metric to describe flows between FAF areas. Equation 3 calculates the proportion, α , of commodity i exported from local community k compared to the total volume of i exported from metacommunity k (both in tons).

$$\alpha_i = \frac{\text{Commodity } i \text{ tonnage export of local community } k}{\text{Total commodity } i \text{ export from metacommunity } k} \quad (3)$$

State-level total commodity consumption rates

In the analogy of a regional economy to an ecosystem, we view the consumption rate of a given commodity within an FAF region as that commodity's "mortality rate." Currently, no data product is available for U.S. commodity-specific consumption rates that can be used in the adapted metacommunity source and sink model (Equation 2). We use the Environmental Protection Agency (EPA) U.S. state-level input-output data and environmentally extended input-output tables for 2017 to calculate the consumption rate (Li et al. 2023). The EPA input-output dataset provides make-use tables that provide the dollar amount of products from one sector required to make products in each other sector. The EPA's state-level dataset provides the highest spatial resolution of available commodity production, use, interregional imports, and interregional export tables (Yang et al. 2017, Ingwersen et al. 2022, Li et al. 2023). The EPA state-level input-output data resolution prohibits us from producing FAF area-specific consumption rates. Because of this data limitation, we assumed uniform consumption rates across FAF regions within the same state. To calculate the consumption rate of each commodity i , we took the total use U_i in a given state from the EPA make-use tables and divided it by the sum of total imports I_i and production P_i (Equation 1). Multiplying this value by 100 gives the consumption rate of that commodity as a percentage of the state's imports and production.

$$\text{Consumption Rate} = \frac{U_i}{I_i + P_i} \times 100 \quad (4)$$

The EPA input-output tables use the North American Industry Classification System (NAICS) codes to track flows between sectors, while the FAF dataset commodities are reported as Standard Classification of Transported Goods (SCTG) codes. To crosswalk between these, we used the Department of Transportation 2017 Commodity Flow Survey, which reports the NAICS code for the origin and destination facilities for each commodity, which is described with an SCTG code. We calculated the proportion flows attached to each NAICS code for each commodity to assign the input-output values to the correct commodities (U.S. Department of Transportation et al. 2023). It is important to note that the crosswalking between NAICS and SCTG commodity codes can potentially produce errors and approximations because of potential inconsistencies, gaps, or reporting errors present in these datasets. Because we are

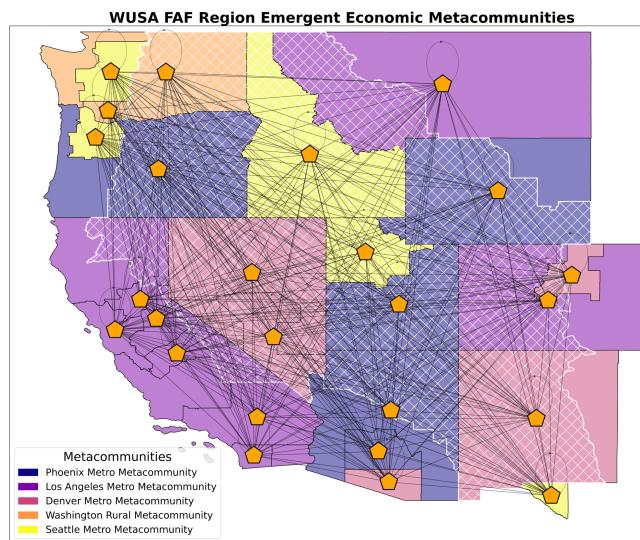
analyzing the total commodities flow rather than individual commodities, we calculated the average consumption rate across all 42 SCTG codes for each state and applied it to the FAF regions found in that state.

RESULTS

Delineating metacommunity structure using trade networks

Figure 2 depicts the 5 emergent economic metacommunities from the WUSA FAF regions commodity flows as identified by the Louvain community detection algorithm. The Louvain algorithm used the modularity metric value of 1, indicating that the trade network partition into metacommunities was strong, highly distinct and not random, with dense connections between community members (Newman 2006, Blondel et al. 2008).

Fig. 2. Five emergent metacommunities comprising 25 Western USA Freight Analysis Framework (FAF) areas identified by the Louvain community detection algorithm. Nodes (pentagons) represent FAF area origins and destinations, with edges indicating the flow of goods between these locations. The white gridded region in the figure represents the boundaries of the Intermountain West region. The circular edges at the nodes represent the self-flows of commodities. The FAF regions are color-coded based on the Louvain community detection algorithm, highlighting regions of closely interconnected supply chain flows.



These emergent economic WUSA metacommunities are not necessarily spatially proximal, demonstrating how trade network connectivity can transcend spatial boundaries. For instance, the Phoenix metro metacommunity is centralized in that the Phoenix-Mesa-Scottsdale, AZ CFS Area (the FAF dataset uses “CFS area” as a part of its regional naming conventions, not to be confused with the CFS dataset) receives most of the imports while the remainder of Arizona, Oregon, Utah, and all of Wyoming export to it (Table 1). Similarly, the Los Angeles metro metacommunity is concentrated around the Los Angeles-Long Beach, CA CFS Area, comprising all 6 FAF regions located in California plus the

Table 1. Lead Freight Analysis Framework (FAF) region importer and exporter of total commodities for each Western USA economic metacommunity.

FAF regions	Percentage of total
Phoenix Metro Metacommunity	
Lead Importer: Phoenix-Mesa-Scottsdale, AZ CFS Area	30.3%
Lead Exporter: Wyoming	30.6%
Los Angeles Metro Metacommunity	
Lead Importer: Los Angeles-Long Beach, CA CFS Area	31.5%
Lead Exporter: Los Angeles-Long Beach, CA CFS Area	28.3%
Denver Metro Metacommunity	
Lead Importer: Denver-Aurora, CO CFS Area	33.6%
Lead Exporter: New Mexico	32.4%
Washington Rural Metacommunity	
Lead Importer: Remainder of Washington	50.04%
Lead Exporter: Remainder of Washington	90.5%
Seattle Metro Metacommunity	
Lead Importer: Seattle-Tacoma, WA CFS Area	39.4%
Lead Exporter: Seattle-Tacoma, WA CFS Area	38.7%

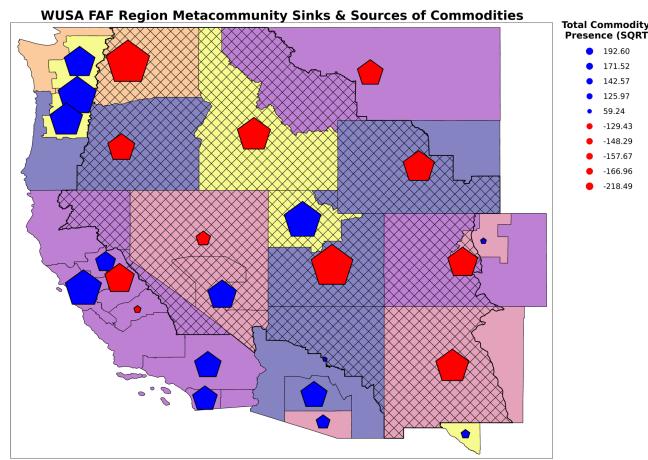
remainder of Colorado and Montana. The Denver metro metacommunity centers around the Denver-Aurora, CO CFS Area as the leading importer with New Mexico and Nevada FAF regions along with the Tucson-Nogales, AZ CFS Area exporting to it. For the Washington rural metacommunity, it consists of the Portland-Vancouver-Salem, OR-WA CFS Area (the WA part) and the remainder of Washington, with the remainder of Washington contributing 90.5% of exports with both regions nearly evenly sharing the total volume of imports. The Seattle metro metacommunity is driven by the primary importer and exporter, Seattle-Tacoma, Washington, but spans Texas, Idaho, Utah, and Oregon. A table with a breakdown of each identified metacommunity and its affiliated FAF regions can be found in the Appendix Supplemental Table 1.

Metacommunity source-sink model

Figure 3 depicts the sinks and sources identified among the 25 WUSA FAF regions using Equation 2. The sources and sinks shown here are analogous to the population sinks and sources across different communities (here, the population includes all “species” of commodities, so it is a very aggregate view). This framing of trade networks allows us to identify the hubs of regional economies and determine which regional economies specialize in the production of raw materials and manufactured products.

FAF areas that consist of an entire state and or a remainder of state region (except the remainder of Arizona) are identified as commodity sinks. Conversely, urban regions tend to be sources. We expect that this is due to industry agglomeration and market size, but also because warehouses and distribution centers are primarily located in urban areas. This means that a region might be a source because of its production/consumption, but also because it acts as an intermediate location or waypoint in the larger trade network. These source and sink results will likely look slightly different when analyzing individual commodities rather than the sum of all commodities. A table of the complete breakdown of input data and output values for all WUSA FAF regions can be found in the Appendix Supplemental Table 2.

Fig. 3. Sources and sinks identified among WUSA subregions using the metacommunity source-sink model. Nodes (pentagons) represent centroids of the FAF regions. The blue and red color of the pentagons represent the source (blue) and sink (red) values for total commodities. The size of the centroid indicates the magnitude of the source/sink dynamic; the values are square root-transformed for visualization scaling. The color of the FAF region indicates its emergent economic metacommunity membership. The black gridded region in the figure represents the boundaries of the IMW area.



State-level commodity consumption rates

Table 2 presents the average consumption rates across SCTG-designated commodities for all 12 states in the study region. Wyoming has the highest average consumption rate of commodities at 28.19%, and Arizona has the lowest rate at 18.86%. These values reflect many factors that vary between states, such as population size, industry specialization, and economic demand. The variation in consumption rates across these states provides high-level insights into regional economic patterns. A breakdown of commodity-specific consumption rates for each of the states is available in the supplemental materials (designated by both SCTG and NAICS codes).

DISCUSSION

Through adapting metacommunity methods to identify metacommunities (Fig. 1) and analyzing their source-sink dynamics (Fig. 3) in the WUSA, we have identified multiscale structures that are not present in other regional trade frameworks (Tamayo and Vargas 2019, Sutton and Arku 2022, Lemke et al. 2023). The model results indicate that the Washington state portion of the Portland-Vancouver-Salem OR-WA CFS, the Salt Lake City-Provo-Orem UT CFS, and the San Jose-San Francisco-Oakland, CA CFS FAF regions are the top three “source” regions for commodities by mass (Table 1). The top three “sink” FAF regions for total commodity tonnage were the remainder of Washington State, the remainder of Utah State, and the entire state of Idaho FAF regions (Table 1). These total commodity-based multi-scalar results reflect local-scale dynamics (e.g., urban centers as sources) and regional-scale interdependencies (e.g., rural areas functioning as sinks). Notably, the identified “source” FAF regions in these emergent economic metacommunities align

Table 2. Average consumption rate across all 42 Standard Classification of Transported Goods commodities by each state in this study.

State	Average commodity consumption rate
Arizona	18.86%
California	23.73%
Colorado	20.34%
Idaho	25.34%
Montana	22.10%
Nevada	20.05%
New Mexico	22.05%
Oregon	24.04%
Texas	23.82%
Utah	25.27%
Washington	24.40%
Wyoming	28.19%

with influential U.S. megaregion counties within the WUSA as identified by Hagler (2009), based on statistical geographic areas, population density, and employment growth metrics. This corroborates the multiscale influence of trade network structures, showing that RER in the WUSA is influenced by local and interregional interactions (Lemke et al. 2023).

When considering total commodity flows, we observe that metro regions are critical “source” regions in WUSA metacommunities because of being key centers for economic activities such as markets, warehouses, consumption of commodities, and logistic activity (Mullins et al. 1999, Pettit and Beresford 2009, Closs et al. 2014). Conversely, all rural sub-regions, with the expectation of the remainder of Arizona, serve as “sink” regions requiring support from “source” regions for total commodity inflows. Although we have determined this “source-sink” relationship of metro and rural regions when using total commodity flows, this may not be the case for individual commodities such as food-based commodities and their embedded water, where rural WUSA regions would emerge as sources. These rural WUSA sub-regions are predominantly major agricultural and raw material producers in their supply chain flows to metro WUSA sub-regions; rural WUSA sub-regions are intertwined and influenced by their supply chain networks with metro WUSA sub-regions (Lawrie et al. 2011, Akkoyunlu 2015, Trujillo and Parilla 2016, Shughrue and Seto 2018, McManamay et al. 2022). Telecoupling between rural and metro regions through trade flows highlights the importance of rural commodity production to the economic hubs of urban regions (Kenessey 1987, Liu et al. 2019). This telecoupling also introduces vulnerabilities, as rural sub-regions may support multiple metro hubs, increasing localized stress on land and resources (McManamay et al. 2022). Therefore, the classification of “source” and “sink” regions oversimplifies the complex, bidirectional relationships between metro and rural areas. Rural regions are not just passive recipients of commodities from metro regions; they are essential sources of products from agriculture, forestry, fishing, hunting, and mining, including minerals, non-mineral energy resources, and renewable energy resources.

Building on this, Moser and Hart (2015) propose an extension of the climatological concept of teleconnections to include eight categories of “societal teleconnections,” which include (1) trade and economic exchange, (2) insurance and reinsurance, (3) energy

systems, (4) food systems; (5) human health, (6) population migration, (7) communication, and (8) strategic alliances and military (Moser and Hart 2015). Utilizing this framing, we can leverage the metacommunity framework to reveal trade and economic exchange teleconnections that link disparate places within states, regions, countries, and globally. This has specific policy implications when analyzing exposure to adverse public policy in other states and countries (e.g., potential price shocks from port shutdowns), vulnerability to cascading risks resulting from non-local natural hazards (e.g., the 2011 floods in Thailand and the price hard drives), or strife between countries (e.g., potential disruption to global pharmaceutical supply chains due to land disputes). By understanding the structure of these teleconnections, policy makers can better prepare for and mitigate such risks in targeted trade networks.

Understanding the interaction patterns and community structure of WUSA regional economies commodity flows is crucial for effectively managing the greater system (Levin 1992). By examining the structural relationships between “source” metro regions and “sink” rural regions, policy makers can target interventions, allocate resources, and manage potential risks more effectively (Kakderi and Tasopoulou 2017). This approach supports the goals of the Endless Frontiers Act, which seeks to identify regional interdependencies and hubs, offering a framework for pinpointing vulnerable sectors, and supporting the development of resilient critical supply chains and industries (U. S Congress 2021). Insights from source-sink dynamics and regional interdependencies aid policy makers in strategically deploying resources to strengthen critical supply chains that are reliant on singular regions and thus improving RER across the U.S. Recognizing that certain metro areas act as critical hubs for total commodity flows to rural regions highlights the need for planners to prioritize infrastructure investments in logistic corridors between these areas. The Bipartisan Infrastructure Law further supports this effort by targeting investments in critical infrastructure such as tunnels, bridges, railways, airports, and ports to withstand future disruptions and enhance national supply chain resilience against future disruptions (The White House 2021). By incorporating the metacommunity analysis, planners can target infrastructure investments for identified vulnerable interdependencies between regions, benefiting local and national networks and promoting sustainable and balanced economic development. This approach strengthens the local resilience of rural regions and bolsters the interconnected domestic regions that rely on one another to meet commodity demands (North 1955, Di Caro and Fratesi 2018, Sutton et al. 2023). By incorporating this understanding of source-sink interdependencies into regional economic planning, policy makers can promote balanced development, reduce over-reliance on specific regions, and ensure that rural and metro areas work together in a mutually reinforcing manner (Giannakis and Bruggeman 2020). A relevant example is the U.S. semiconductor industry, where Arizona has become the primary hub for domestic semiconductor manufacturing, with facilities in New Mexico and Oregon serving as secondary hubs that bolster the resilience of the greater domestic U.S. semiconductor manufacturing network. The insights provided in this study allow for the development of nuanced strategies to address regional disparities in demand,

production, disaster recovery, and risk management. Further, it emphasizes the importance of interregional interactions in shaping RER, ensuring both rural and metro regions contribute to and benefit from economic resilience (Di Caro and Fratesi 2018).

In its current form, the model has several limitations that can impact the accuracy and representation of the real-world WUSA regional economic trade network. First, the crosswalking between NAICS and SCTG commodity codes produces potential errors and approximations of the potential inconsistencies, gaps, or reporting errors in these datasets. These potential issues could misallocate the commodity flows between FAF regions, impacting the source-sink results. The model also assumes a uniform storage capacity ($V_k = 1$) across all WUSA regions because of the lack of available detailed storage. This assumption results in our model considering storage capacity as a linear flow. This simplification fails to account for regional variability in storage capacity, which would impact commodity flows, especially during disruptions where storage buffers are critical. However, the storage data issue is unknown and will likely persist until more detailed and targeted data collection occurs (Gardner et al. 2019). Because the global economy largely operates in a just-in-time manner, it remains to be seen how big of an issue not possessing storage data is (Choi et al. 2023). Additionally, the scale of this issue will not be known until the storage of each commodity is known. Another limitation is the uniformity of state-level consumption rates across all FAF regions within a state. This simplification masks the variation in economic activity and resource consumption, not accurately reflecting the actual consumption patterns across the WUSA. Future models will be able to address this using the upcoming U.S. Department of Transportation and Oak Ridge National Laboratory publication of county-level FAF data that is not subject to trade downscaling model artifacts. However, without finer resolution input-output datasets, the current state-level resolution is the finest spatial scale available. Furthermore, although the model can incorporate disruptions through the import success (θ) parameter, it does not incorporate any capacity to account for regulatory or political factors, such as tariffs or transportation policies, which can influence commodity movement. Collectively, these limitations reduce the model’s ability to reflect the complexity and variability of the real-world WUSA regional economic network.

Future work that builds on this study can address the limitations with more granular data and refine the simplifications and assumptions made in this study. Although simplifying all commodities into a total commodity value to be represented as a single species and demonstrate the model potential, it masks the unique interaction and community structure of different commodities. A future question to answer is whether different emergent metacommunities are identified based on commodity flow tonnage or dollar connectivity. Future work should model each commodity as a unique species in the model to produce the metacommunity structure and the source-sink insights for each commodity. Additionally, this study only explores a temporal snapshot for 2017, which is not representative of the dynamic nature of economic complex systems. Future work should aim to model a greater temporal window of several years or at a monthly temporal scale if the data is available. This extended temporal

window would show how commodity-based metacommunities would or would not dynamically change in response to domestic and international disruptions. Improving the spatial resolution by using county-level data in place of FAF regions would expand the analysis from 25 FAF regions to 668 county polygons. Although the data required for this is currently unavailable, this would be one of the largest improvement aspects for this model framework. Additionally, assuming all imports arrive with 100% success removes the dispersal success parameter (θ), which can lead to an overly optimistic view of regional economic trade resilience. Incorporating disruptions could make the model more robust and realistic. However, it is uncertain if the reported FAF commodity values have had disruption incorporated into their reported values. Last, it should be noted that although we focus on domestic commodity flows in our analysis of the WUSA trade network, it is likely that the metacommunities also have critical international connections that could shift our interpretation of interdependencies; for example, Seattle, Washington, is very integrated with Vancouver, Canada through measures like the Cascadia Economic Development Agreement (VEC 2019). However, we currently lack similar resolution data from Mexico and Canada. Future work could focus on identifying metacommunities continentally or globally, pending data availability.

Fruitful avenues of future research could examine the sustainability and resilience of individual regions considering the regional interdependencies and the roles played within the larger network. Additionally, investigating the applied consequences of being a source or sink will help us better understand the strengths and weaknesses of these roles and how they impact regional economic development. Further research could explore the development of transboundary policy tools designed to better manage a regional networked metacommunity, assessing policies related to resource management, infrastructure investment, and trade agreements that can be tailored to support regional interconnections and address potential resource bottlenecks. An important area for future work would be integrating the metacommunity insights into macroeconomic models, exploring how the source-sink relationships between regions impact national economic indicators like GDP, employment, and trade balances. This could offer a more comprehensive view of how regional interactions influence broader national and global economic outcomes.

By incorporating insights from economics, ecology, and network science, we have developed an approach to identify a regional system's metacommunity structure to highlight ecologic and economic interdependencies. Potential insights from applying the metacommunity framework to regional trade networks include showing the change in resilience achieved by diversifying regional trade partners, promoting critical infrastructure development, and developing sustainable practices that benefit rural and metro regions. In the context of the special feature, the metacommunity framing of a regional system, including the WUSA, supports convergence research focused on sustainable regional systems and guided transformations in this region by creating a common language and quantitative framework for observing the structure of this system (Morgan et al. 2024, 2025).

CONCLUSION

This study advances the understanding of spatial patterns of trade relationships in the WUSA using theory and methods from (meta)community ecology. Combining network theory and community ecology constitutes a biomimetic, social-ecological systems approach to investigating and designing regional economic structure. Our identification of economic metacommunities through commodity flows, as distinct from previously identified “megaregions,” establishes a new avenue for investigating the economic network structures that underlie trade resilience and sustainability. Our study bridges theoretical perspectives between ecologic and economic networks and outlines a novel method for delineating regional economic metacommunities to support policy development and regional planning.

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Data Availability:

The data and code that support the findings of this study are openly available here: https://github.com/Sjostedt-eric/Regional_Metacommunities. Supplementary files can be found at <https://zenodo.org/records/14205978>.

LITERATURE CITED

Akkoyunlu, S. 2015. The potential of rural-urban linkages for sustainable development and trade. *International Journal of Sustainable Development & World Policy* 4(2):20-40. <https://doi.org/10.18488/journal.26/2015.4.2/26.2.20.40>

Barabás, G., M. J. Michalska-Smith, and S. Allesina. 2017. Self-regulation and the stability of large ecological networks. *Nature Ecology & Evolution* 1(12):1870-1875. <https://doi.org/10.1038/s41559-017-0357-6>

Blondel, V. D., J. L. Guillaume, R. Lambiotte, and E. Lefebvre. 2008. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment* 2008(10):P10008. <https://doi.org/10.1088/1742-5468/2008/10/P10008>

Boulatoff, C., T. B. İşcan, and Y. Kotlyarova. 2022. Does distance matter for trade in services? The case of interprovincial trade in Canada. *Open Economies Review* 33:157-185. <https://doi.org/10.1007/s11079-021-09629-3>

Brei, M., and G. von Peter. 2018. The distance effect in banking and trade. *Journal of International Money and Finance* 81:116-137. <https://doi.org/10.1016/j.jimfin.2017.10.002>

Bristow, G., and A. Healy. 2020. Introduction to the handbook on regional economic resilience. Pages 1-8 in G. Bristow and A. Healy, editors. *Handbook on regional economic resilience*. Edward Elgar, Cheltenham, UK. <https://doi.org/10.4337/9781785360862.00005>

Cainelli, G., R. Ganau, and M. Modica. 2019. Industrial relatedness and regional resilience in the European Union. *Papers in Regional Science* 98(2):755-779. <https://doi.org/10.1111/pirs.12377>

Cedillo-Campos, M. G., C. Sánchez-Ramírez, S. Vadali, J. C. Villa, and M. B. Menezes. 2014. Supply chain dynamics and the “cross-border effect”: The US-Mexican border’s case. *Computers & Industrial Engineering* 72:261-273. <https://doi.org/10.1016/j.cie.2014.03.015>

Chapin III, F. S., P. A. Matson, and H. A. Mooney. 2002. *Principles of terrestrial ecosystem ecology*. Springer-Verlag, New York, New York, USA. <https://doi.org/10.1007/b97397>

Choi, T. Y., T. H. Netland, N. Sanders, M. S. Sodhi, and S. M. Wagner. 2023. Just-in-time for supply chains in turbulent times. *Production and Operations Management* 32(7):2331-2340. <https://doi.org/10.1111/poms.13979>

Closs, D. J., Y. A. Bolumole, and F. Rodammer. 2014. Supply chain management opportunities for regional economic development. *Transportation Journal* 53(4):453-498. <https://doi.org/10.5325/transportationj.53.4.0453>

Davis, K. F., S. Downs, and J. A. Gephart. 2021. Towards food supply chain resilience to environmental shocks. *Nature Food* 2(1):54-65. <https://doi.org/10.1038/s43016-020-00196-3>

de Chalendar, J. A., J. Taggart, and S. M. Benson. 2019. Tracking emissions in the US electricity system. *Proceedings of the National Academy of Sciences* 116(51):25497-25502. <https://doi.org/10.1073/pnas.1912950116>

Di Caro, and U. Fratesi. 2018. Regional determinants of economic resilience. *Annals of Regional Science* 60:235-240. <https://doi.org/10.1007/s00168-017-0858-x>

Doğan, N. B., A. Mejia, and M. Gomez. 2023. Cities can benefit from complex supply chains. *npj Urban Sustainability* 3(1):20. <https://doi.org/10.1038/s42949-023-00100-5>

Erkman, S. 1997. Industrial ecology: an historical view. *Journal of Cleaner Production* 5(1-2):1-10. [https://doi.org/10.1016/S0959-6526\(97\)00003-6](https://doi.org/10.1016/S0959-6526(97)00003-6)

Evenhuis, E., and S. Dawley. 2017. Evolutionary perspectives on economic resilience in regional development. Pages 192-205 in N. Williams and T. Vorley, editors. *Creating resilient economies*. Edward Elgar, Cheltenham, UK. <https://doi.org/10.4337/9781785367649.00020>

Feng, Y., C. C. Lee, and D. Peng. 2023. Does regional integration improve economic resilience? Evidence from urban agglomerations in China. *Sustainable Cities and Society* 88:104273. <https://doi.org/10.1016/j.scs.2022.104273>

Filipovitch, A. J. 2023. Megaregions and America’s future, by Robert D. Yaro, Ming Zhang and Frederick R. Steiner: Cambridge, MA, Lincoln Institute of Land Policy, 2022. *Journal of Urban Affairs* 45(4):899-901. <https://doi.org/10.1080/07352166.2022.2113721>

Fingleton, B., H. Garretsen, and R. Martin. 2012. Recessionary shocks and regional employment: evidence on the resilience of UK regions. *Journal of Regional Science* 52(1):109-133. <https://doi.org/10.1111/j.1467-9787.2011.00755.x>

Garcia, S., and A. Mejia. 2019. Characterizing and modeling subnational virtual water networks of US agricultural and industrial commodity flows. *Advances in Water Resources* 130:314-324. <https://doi.org/10.1016/j.advwatres.2019.06.013>

Garcia, S., R. R. Rushforth, B. L. Ruddell, and A. Mejia. 2020. Full domestic supply chains of blue virtual water flows estimated for major US cities. *Water Resources Research* 56(4):e2019WR026190. <https://doi.org/10.1029/2019WR026190>

Gardner, T., M. Benzie, J. Börner, E. Dawkins, S. Fick, R. Garrett, J. Godar, A. Grimard, S. Lake, R. Larsen, et al. 2019. Transparency and sustainability in global commodity supply chains. *World Development* 121:163-177. <https://doi.org/10.1016/j.worlddev.2018.05.025>

Gephart, J. A., E. Rovenskaya, U. Dieckmann, M. L. Pace, and Å. Brännström. 2016. Vulnerability to shocks in the global seafood trade network. *Environmental Research Letters* 11(3):035008. <https://doi.org/10.1088/1748-9326/11/3/035008>

Giannakis, E., and A. Bruggeman. 2020. Regional disparities in economic resilience in the European Union across the urban-rural divide. *Regional Studies* 54(9):1200-1213. <https://doi.org/10.1080/00343404.2019.1698720>

Gomez, M., A. Mejia, B. L. Ruddell, and R. R. Rushforth. 2021. Supply chain diversity buffers cities against food shocks. *Nature* 595(7866):250-254. <https://doi.org/10.1038/s41586-021-03621-0>

Gottmann, J. 1957. Megalopolis or the urbanization of the northeastern seaboard. *Economic Geography* 33(3):189-200. <https://doi.org/10.2307/142307>

Graedel, T. E. 1996. On the concept of industrial ecology. *Annual Review of Energy and the Environment* 21(1):69-98. <https://doi.org/10.1146/annurev.energy.21.1.69>

Gruner, R. L., and D. Power. 2017. Mimicking natural ecosystems to develop sustainable supply chains: a theory of socio-ecological intergradation. *Journal of Cleaner Production* 149:251-264. <https://doi.org/10.1016/j.jclepro.2017.02.109>

Hagler, Y. 2009. Defining US megaregions. *America* 2050:1-8.

He, M., J. Glasser, N. Pritchard, S. Bhamidi, and N. Kaza. 2020. Demarcating geographic regions using community detection in commuting networks with significant self-loops. *PLoS ONE* 15(4): e0230941. <https://doi.org/10.1371/journal.pone.0230941>

Heino, J., A. S. Melo, T. Siqueira, J. Soininen, S. Valanko, and L. M. Bini. 2015. Metacommunity organisation, spatial extent and dispersal in aquatic systems: patterns, processes and prospects. *Freshwater Biology* 60(5):845-869. <https://doi.org/10.1111/fwb.12533>

Helmrich, A. M., M. V. Chester, S. Hayes, S. A. Markolf, C. Desha, and N. B. Grimm. 2020. Using biomimicry to support resilient infrastructure design. *Earth's Future* 8(12):e2020EF001653. <https://doi.org/10.1029/2020EF001653>

Holland, J. H. 1992. Complex adaptive systems. *Daedalus* 121:17-30.

Holling, C. S. 1973. Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics* 4(1):1-23. <https://doi.org/10.1146/annurev.es.04.110173.000245>

Holt, R. D. 1985. Population dynamics in two-patch environments: some anomalous consequences of an optimal habitat distribution. *Theoretical Population Biology* 28(2):181-208. [https://doi.org/10.1016/0040-5809\(85\)90027-9](https://doi.org/10.1016/0040-5809(85)90027-9)

Hwang, H. L., H. Lim, S. M. Chin, M. Uddin, A. Biehl, F. Xie, S. Hargrove, Y. Liu, and R. Wang. 2021. Freight analysis framework Version 5 (FAF5) Base Year 2017 Data Development Technical Report (No. ORNL/TM-2021/2154). Oak Ridge National Lab, Oak Ridge, Tennessee, USA. <https://doi.org/10.2172/1844893>

Ingwersen, W. W., M. Li, B. Young, J. Vendries, and C. Birney. 2022. USEEIO v2. 0, the US environmentally-extended input-output model v2. 0. *Scientific Data* 9(1):194. <https://doi.org/10.1038/s41597-022-01293-7>

Jacobson, B., and P. R. Peres-Neto. 2010. Quantifying and disentangling dispersal in metacommunities: how close have we come? How far is there to go? *Landscape Ecology* 25:495-507. <https://doi.org/10.1007/s10980-009-9442-9>

Kakderi, C., and A. Tasopoulou. 2017. Regional economic resilience: the role of national and regional policies. *European Planning Studies* 25(8):1435-1453. <https://doi.org/10.1080/096543-13.2017.1322041>

Kenessey, Z. 1987. The primary, secondary, tertiary and quaternary sectors of the economy. *Review of Income and Wealth* 33(4):359-385. <https://doi.org/10.1111/j.1475-4991.1987.tb00680.x>

Kharrazi, A., E. Rovenskaya, and B. D. Fath. 2017. Network structure impacts global commodity trade growth and resilience. *PLoS ONE* 12(2):e0171184. <https://doi.org/10.1371/journal.pone.0171184>

Kharrazi, A., E. Rovenskaya, B. D. Fath, M. Yarime, and S. Kraines. 2013. Quantifying the sustainability of economic resource networks: an ecological information-based approach. *Ecological Economics* 90:177-186. <https://doi.org/10.1016/j.ecolecon.2013.03.018>

Lant, C., S. Paudel, K. Mueller, G. Larson, G. A. Ovando-Montejo, and J. Givens. 2023. Allocation of US biomass production to food, feed, fiber, fuel and exports. *Land* 12(3):695. <https://doi.org/10.3390/land12030695>

Lawrie, M., M. Tonts, and P. Plummer. 2011. Boomtowns, resource dependence and socio-economic well-being. *Australian Geographer* 42(2):139-164. <https://doi.org/10.1080/00049182.2011.569985>

Legenvre, H., A. P. Hameri, and R. Golini. 2022. Ecosystems and supply chains: how do they differ and relate. *Digital Business* 2(2):100029. <https://doi.org/10.1016/j.digbus.2022.100029>

Leibold, M. A., and J. M. Chase. 2018. Metacommunity ecology. *Monographs in population biology* Volume 59. Princeton University Press, Princeton, New Jersey, USA. <https://doi.org/10.1515/9781400889068>

Leibold, M. A., M. Holyoak, N. Mouquet, P. Amarasekare, J. M. Chase, M. F. Hoopes, R. D. Holt, J. B. Shurin, R. Law, D. Tilman, M. Loreau, and A. Gonzalez. 2004. The metacommunity concept: a framework for multi-scale community ecology. *Ecology Letters* 7(7):601-613. <https://doi.org/10.1111/j.1461-0248.2004.00608.x>

Lemke, L. K. G., P. Sakdapolrak, and M. Trippel. 2023. Unresolved issues in regional economic resilience: conceptual ways forward. *Progress in Human Geography* 47(5):699-717. <https://doi.org/10.1177/03091325231191242>

Levin, S. A. 1992. The problem of pattern and scale in ecology: the Robert H. MacArthur award lecture. *Ecology* 73(6):1943-1967. <https://doi.org/10.2307/1941447>

Levins, R. 1969. Some demographic and genetic consequences of environmental heterogeneity for biological control. *Bulletin of the Entomological Society of America* 15(3):237-240. <https://doi.org/10.1093/besa/15.3.237>

Li, M., J. P. Ferreira, C. D. Court, D. Meyer, M. Li, and W. W. Ingwersen. 2023. State IO-open source economic input-output models for the 50 states of the United States of America. *International Regional Science Review* 46(4):428-481. <https://doi.org/10.1177/01600176221145874>

Lin, X., P. J. Ruess, L. Marston, and M. Konar. 2019. Food flows between counties in the United States. *Environmental Research Letters* 14(8):084011. <https://doi.org/10.1088/1748-9326/ab29ae>

Liu, J., A. Herzberger, K. Kapsar, A. K. Carlson, and T. Connor. 2019. What is telecoupling? Pages 19-48 in C. Friis and J. Ø. Nielsen, editors. *Telecoupling: exploring land-use change in a globalised world*. Palgrave Macmillan, Cham, Switzerland. https://doi.org/10.1007/978-3-030-11105-2_2

Liu, S. and E. Kontou. 2022. Quantifying transportation energy vulnerability and its spatial patterns in the United States. *Sustainable Cities and Society* 82:103805. <https://doi.org/10.1016/j.scs.2022.103805>

MacArthur, R. 1955. Fluctuations of animal populations and a measure of community stability. *Ecology* 36(3):533-536. <https://doi.org/10.2307/1929601>

Martin, R.: Sunley, B. Gardiner, and P. Tyler. 2016. How regions react to recessions: resilience and the role of economic structure. *Regional Studies* 50(4):561-585. <https://doi.org/10.1080/003434-04.2015.1136410>

McManamay, R. A., C. Brinkley, C. R. Vernon, S. Raj, and J. S. Rice. 2022. Urban land teleconnections in the United States: a graphical network approach. *Computers, Environment and Urban Systems* 95:101822. <https://doi.org/10.1016/j.compenvurbsys.2022.101822>

Mittelbach, G. G., and B. J. McGill. 2019. *Community ecology*. Oxford University Press, Oxford, UK. <https://doi.org/10.1093/oso/9780198835851.001.0001>

Moiz, T. 2022. Spatially resolved carbon dioxide emissions estimations for gasoline and diesel in the US. Dissertation. Arizona State University, Tempe, Arizona, USA.

Moore, J. F. 1993. Predators and prey: a new ecology of competition. *Harvard Business Review* 71(3):75-86.

Morgan, M., Y. C. Lin, M. Walsh-Dilley, A. J. Webster, A. B. Stone, K. Chief, N. G. Estrada, K. Ayers, H. Love, P. A. Townsend, S. A. Hall, R. R. Rushforth, R. R. Morrison, J. Boll, and M. C. Stone. 2025. Convergence, transdisciplinarity and team science: an interepistemic approach. *Ecology and Society* 30(1):3. <https://doi.org/10.5751/ES-15492-300103>

Morgan, M., A. J. Webster, J. C. Padowski, R. R. Morrison, C. G. Flint, K. Simmons-Potter, K. Chief, B. Litson, B. Neztsosie, V. Karanikola, M. Kacira, R. R. Rushforth, J. Boll, and M. B. Stone. 2024. Guided transformations for communities facing social and ecological change. *Ecology and Society* 29(4):20. <https://doi.org/10.5751/ES-15448-290420>

Moser, S. C., and J. A. F. Hart. 2015. The long arm of climate change: societal teleconnections and the future of climate change impacts studies. *Climatic Change* 129(1):13-26. <https://doi.org/10.1007/s10584-015-1328-z>

Mouquet, N., and M. Loreau. 2003. Community patterns in source-sink metacommunities. *American Naturalist* 162(5):544-557. <https://doi.org/10.1086/378857>

Mullins, P., K. Natalier, P. Smith, and B. Smeaton. 1999. Cities and consumption spaces. *Urban Affairs Review* 35(1):44-71. <https://doi.org/10.1177/10780879922184284>

Nelson, G. D., and A. Rae. 2016. An economic geography of the United States: from commutes to megaregions. *PLoS ONE* 11(11):e0166083. <https://doi.org/10.1371/journal.pone.0166083>

Newman, M. E. 2006. Modularity and community structure in networks. *Proceedings of the National Academy of Sciences* 103(23):8577-8582. <https://doi.org/10.1073/pnas.0601602103>

Newman, M. E., and M. Girvan. 2004. Finding and evaluating community structure in networks. *Physical Review E* 69(2):026113. <https://doi.org/10.1103/PhysRevE.69.026113>

North, D. C. 1955. Location theory and regional economic growth. *Journal of Political Economy* 63(3):243-258. <https://doi.org/10.1086/257668>

Paudel, S., K. Mueller, G. Ovando-Montejo, R. Rushforth, L. Tango, and C. Lant. 2023. Product-specific human appropriation of net primary production in US counties. *Ecological Indicators* 150:110241. <https://doi.org/10.1016/j.ecolind.2023.110241>

Pettit, S. J., and A. K. C. Beresford. 2009. Port development: from gateways to logistics hubs. *Maritime Policy & Management* 36(3):253-267. <https://doi.org/10.1080/03088830902861144>

Pickett, S. T., M. L. Cadenasso, J. M. Grove, C. H. Nilon, R. V. Pouyat, R. W. C. Zipperer, and R. Costanza. 2001. Urban ecological systems: linking terrestrial ecological, physical, and socioeconomic components of metropolitan areas. *Annual Review of Ecology and Systematics* 32(1):127-157. <https://doi.org/10.1146/annurev.ecolsys.32.081501.114012>

Pulliam, H. R. 1988. Sources, sinks, and population regulation. *American Naturalist* 132(5):652-661. <https://doi.org/10.1086/284880>

Raimi, D., S. Carley, and D. Konisky. 2022. Mapping county-level vulnerability to the energy transition in US fossil fuel communities. *Scientific Reports* 12(1):15748. <https://doi.org/10.1038/s41598-022-19927-6>

Rushforth, R. R., and B. L. Ruddell. 2018. A spatially detailed blue water footprint of the United States economy. *Hydrology and Earth System Sciences* 22(5):3007-3032. <https://doi.org/10.5194/hess-22-3007-2018>

Simmie, J., and R. Martin. 2010. The economic resilience of regions: towards an evolutionary approach. *Cambridge Journal of Regions, Economy and Society* 3(1):27-43. <https://doi.org/10.1093/cjres/rsp029>

Simonson, A. 2023. Utah's inland port: the future of logistics in the intermountain region or gambling with taxpayer money. *Undergraduate Honors Theses* 298. Marriott School of Management, Provo, Utah, USA. https://scholarsarchive.byu.edu/studentpub_uht/298

Shmida, A. V. I., and M. V. Wilson. 1985. Biological determinants of species diversity. *Journal of Biogeography* 12:1-20. <https://doi.org/10.2307/2845026>

Shughrue, C., and K. C. Seto. 2018. Systemic vulnerabilities of the global urban-industrial network to hazards. *Climatic Change* 151(2):173-187. <https://doi.org/10.1007/s10584-018-2293-0>

Smetana, S., C. Tamásy, A. Mathys, and V. Heinz. 2015. Sustainability and regions: sustainability assessment in regional perspective. *Regional Science Policy & Practice* 7(4):163-187. <https://doi.org/10.1111/rsp3.12068>

Sutton, J., A. Arcidiacono, G. Torrisi, and R. N. Arku. 2023. Regional economic resilience: a scoping review. *Progress in Human Geography* 47(4):500-532. <https://doi.org/10.1177/0309-1325231174183>

Sutton, J., and G. Arku. 2022. Regional economic resilience: towards a system approach. *Regional Studies, Regional Science* 9(1):497-512. <https://doi.org/10.1080/21681376.2022.2092418>

Tamayo, U., and G. Vargas. 2019. Biomimetic economy: human ecological-economic systems emulating natural ecological systems. *Social Responsibility Journal* 15(6):772-785. <https://doi.org/10.1108/SRJ-09-2018-0241>

Taubenböck, H., and M. Wiesner. 2015. The spatial network of megaregions: types of connectivity between cities based on settlement patterns derived from EO-data. *Computers, Environment and Urban Systems* 54:165-180. <https://doi.org/10.1016/j.compenvurbsys.2015.07.001>

The White House. 2021. A guidebook to the Bipartisan Infrastructure Law. The White House, Washington, D.C., USA. <https://www.whitehouse.gov/build/guidebook/>

Trujillo, J. L., and J. Parilla. 2016. Redefining global cities: the seven types of global metro economies. Brookings Institution, Washington, D.C., USA.

Turken, N., V. Cannataro, A. Geda, and A. Dixit. 2020. Nature inspired supply chain solutions: definitions, analogies, and future research directions. *International Journal of Production Research* 58(15):4689-4715 <https://doi.org/10.1080/00207543.2020.1778206>

U.S. Congress. 2021. Endless Frontier Act, S.1260, 117th Congress (2021). U.S. Congress, Washington, D.C., USA. <https://www.congress.gov/bill/117th-congress/house-bill/2731>

U.S. Department of Transportation, Bureau of Transportation Statistics, U.S. Department of Commerce, U.S. Census Bureau. 2023. 2017 Commodity flow survey final tables. Washington, D. C., USA. <https://www.census.gov/data/tables/2017/econ/cfs/aff-2017.html>

Vancouver Economic Commission (VEC). 2019. Vancouver Economic Commission Greater Seattle Partners Cascadia Economic Development Agreement., VEC, Vancouver, British Columbia, Canada. <https://vancouvereconomic.com/wp-content/uploads/2019/10/2b50c4d1-cascadia-economic-development-agreement-signed.pdf>

Verschuur, J., E. E. Koks, and J. W. Hall. 2022. Ports' criticality in international trade and global supply-chains. *Nature Communications* 13(1):4351. <https://doi.org/10.1038/s41467-022-32070-0>

Wagg, C., C. Roscher, A. Weigelt, A. Vogel, A. Ebeling, E. De Luca, A. Roeder, C. Kleinspehn, V. M. Temperton, S. T. Meyer, et al. 2022. Biodiversity-stability relationships strengthen over time in a long-term grassland experiment. *Nature Communications* 13(1):7752. <https://doi.org/10.1038/s41467-022-35189-2>

Walker, B., A. Kinzig, and J. Langridge. 1999. Plant attribute diversity, resilience, and ecosystem function: the nature and significance of dominant and minor species. *Ecosystems* 2:95-113. <https://doi.org/10.1007/s100219900062>

Wieland, A., M. Stevenson, S. A. Melnyk, S. Davoudi, and L. Schultz. 2023. Thinking differently about supply chain resilience: what we can learn from social-ecological systems thinking. *International Journal of Operations & Production Management* 43(1):1-21. <https://doi.org/10.1108/IJOPM-10-2022-0645>

Wilmsmeier, G., J. Monios, and B. Lambert. 2011. The directional development of intermodal freight corridors in relation to inland terminals. *Journal of Transport Geography* 19(6):1379-1386. <https://doi.org/10.1016/j.jtrangeo.2011.07.010>

World Commission on Environment and Development (WCED). 1987. Report of the World Commission on Environment and Development: our common future. <https://sustainabledevelopment.un.org/content/documents/5987our-common-future.pdf>

Yang, Y., W. W. Ingwersen, T. R. Hawkins, M. Srocka, and D. E. Meyer. 2017. USEEIO: a new and transparent United States environmentally-extended input-output model. *Journal of Cleaner Production* 158:308-318. <https://doi.org/10.1016/j.jclepro.2017.04.150>

Zhang, M., and B. Lan. 2022. Detect megaregional communities using network science analytics. *Urban Science* 6(1):12. <https://doi.org/10.3390/urbansci6010012>

Appendix 1. Trade-based megaregion communities identified by the Louvain community detection algorithm.

[Please click here to download file 'appendix1.csv'.](#)

Appendix 2. All WUSA sub-regions with the parameters required for the metacommunity sink-source model and the model output parameter of presence.

[Please click here to download file 'appendix2.csv'.](#)
