Research, Education, Action, And Policy For Resilience (REAP Resilience)

Our vision is to build a community-led information co-production platform (REAP) to support a healthy, equitable and resilient (HER) food system (FS) in Western New York (WNY)[1].

A food system (FS) is the soil-to-soil system that encompasses production, processing, distribution, acquisition and consumption of food; and management of food-related waste. A complex network of stakeholders, resources, activities, and information move food from farm to plate. Although the US's FS have many strengths, they are also frayed [12]. Consider a few examples pertinent to WNY. Food insecurity impacts both urban and rural communities. In 2020, about 92,898 households depended on the Supplemental Nutrition Assistance Program (SNAP) in Erie and Niagara. It has been estimated by WNY's regional food bank that during the COVID-19 pandemic as many as one in six people may be at risk of hunger throughout its service area [52]. In the Buffalo metropolitan area, nearly 56,000 households, or 12 percent of all households, lack access to a supermarket (i.e., live beyond the average 0.4 mile walking distance for shopping and do not have access to a personal vehicle). Low nutrient, hyper-processed foods are readily and cheaply available, while high nutrition foods are hard to come by in low-income neighborhoods [53]. Consolidation in food industry networks has shortchanged farmers, consumers, and workers [25, 36]. Farming is a high risk business, especially for small and medium sized farms [61]. Times of instability, such as the COVID-19 pandemic, further fray food networks. Food-related comorbidities exacerbate health inequities even further for Black, brown and lower-income people [49].

Because of these inequities, food systems have been drawing increasing attention from policy makers in the last 2 decades [54], and attention to rebuilding HER food systems is even more recent [65, 11]. In a healthy, equitable, and resilient regional FS, the environmental, economic, social, and nutritional health of residents is protected in both routine and crisis conditions, allowing not just system recovery, but in fact improvement after the crisis. For example, during the acute phase of the COVID pandemic in March 2020, disruptions in supply networks led to supermarkets and grocery stores running out of particular foods [26]. People who were unable to travel (e.g., the elderly or those without cars) had to depend on food retail located in proximity to their homes. Fluctuations in demand from large-scale buyers led to farmers (especially in the dairy industry) dumping their produce. These challenges and many others triggered a community-led effort called Seeding Resilience in Buffalo, NY. Co-convened by co-PI Raja, this effort responded rapidly with the goal of increasing food production, jobs, and distribution of food through emergency distribution channels [49]. Raja and colleagues also created an online map to help residents locate food resources, subject to cost and distance constraints. Residents in need could locate accessible sources of free food [1]. This map was not only a resource for some of the hardest-hit residents, but also guided philanthropists and policymakers to better distribute scarce resources.

Inspired (in part by Seeding Resilience), a regional, nine-county, community-led effort called the WNY Regional Food Systems Initiative (WNY RFSI), involving the PIs, is working to plan and build a more extensive **regional-scale** mapping system. This collaboration facilitates inclusive planning processes, where stakeholders in a region's food system co-design the portals that map and monitor problems, and in doing so address the sustainability of seeding resilience. However, WNY RFSI's mandate is primarily data aggregation and policy guidance, rather than collection and maintenance of food system data. The infrastructure established by WNY RFSI stands to become significantly more effective if coupled with **sustainable, reliable processes for keeping the available data fresh and up-to-date**. A sustainable process for data collection must be rooted in community engagement; In contrast to the static, "unidirectional" Seeding Resilience

[1]Western New York comprises nine counties of Allegany, Genesee, Orleans, Niagara, Erie, Monroe, Chattaraugus, Chautauqua, and Wyoming and its constituent cities, villages, and towns.

and WNY RFSI projects, we propose a data cycle, where community members co-produce data that directly benefits them. Achieving this cycle requires addressing several technological and sociological challenges: (i) it must be easy for community members to contribute data, (ii) we must understand how increasing community engagement will shape the food system, (iii) the limitations of crowdsourced data and how they impact derived artifacts must be understood, and above all else (iv) data collection objectives must be rooted in the needs of the community. Our proposal seeks to develop an app (REAP) to facilitate information co-production for the WNY FS. We will build on the existing data portal being developed in collaboration between the PIs and WNY RFSI (see support letter: Gosch), adding an interactive personalized presentation layer and crowdsourced data collection tools. Our goal for this planning proposal is to tackle four specific challenges, and in doing so, to lay the groundwork for a successful community hub, moving forward.

Broader Impacts

REAP will aid multiple groups in making practical, strategic, and policy decisions within WNY. Residents in WNY will be able to readily locate food resources—by price and type—within their vicinity. Wholesale and retail food vendors within the region can efficiently identify—and ultimately procure—local and/or regional produce, triggering increased circulation of dollars within the region. Finally, the portal will aid food policy councils, food networks, public agencies, and philanthropic organizations to identify spatial areas in WNY that are most in need of resources and investment.

Integrative Research

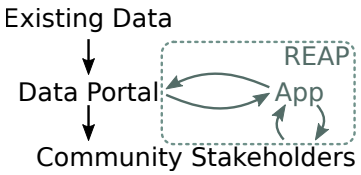

Figure 1: **REAP facilitates data co-production by community stakeholders.**

Based on our experiences with the Seeding Resilience data mapping portal (for Buffalo, NY), we have already identified several data collection objectives from the broader WNY community for REAP: (i) **Tracking up-to-date information about seasonal and spatial availability of fresh food** (e.g., when/where are locally grown vegetables available) helps community members to find nearby sources of healthy food (e.g., when a store closes or runs out of a staple), while also helping planners to address shortfalls when needed; (ii) information about **the availability of fresh food in retail stores and farm stands** can be used by planners to identify gaps in the WNY food system, while simultaneously guiding community members towards healthier food options. We will work with WNY RFSI facilitators to develop an app that will (i) provide personalized access to the WNY RFSI portal (to motivate users to download the app), and (ii) provide easy-to-use tools that (e.g., when gamified [29]) encourage community members to contribute data back to the portal. In this section, we outline four specific technical and sociological challenges that need to be overcome in order to deploy and leverage REAP, our primary objective in this planning proposal. As part of this deployment process, we will convene an advisory board (discussed below) to guide the development of REAP, assist with community deployment, and aid in developing research objectives for a forthcoming SCC-IRG proposal. Once deployed, REAP will be able to bootstrap a broader research agenda, a platform for deploying a wider range of community data co-production and data-dissemination efforts, and a prototype for similar efforts in other communities.

Research Questions

In addition to its direct benefits to the WNY food system, REAP will facilitate unique convergent research questions that are responsive to chronic racial and economic inequities and instabilities in the WNY food system, recently exacerbated by COVID 19. These questions will be addressed by a team of interdisciplinary researchers working alongside community-based investigators.

Image Recognition for Food Resource Monitoring

Figure 2: **Images may include distractors (e.g., "TOMATOES") or irrelevant labels (e.g., "great for stuffing").**

To capture reliable information pertaining to availability and pricing of food, a continuous feed of real-time data crowd-sourced from volunteers is necessary. Facilitating the collection of large amounts of user provided data requires a seamless pipeline to perform hassle-free extraction of relevant information. The primary source of data, in this application, constitutes images of produce displays—from retail stores to farm stands—possibly including item display labels and/or prices that are captured and submitted by users. We expect that state-of-the-art machine learning and computer vision algorithms for scene text and object recognition including techniques developed under our current NSF-funded (OAC-1640867) grant [31, 32, 64, 30, 28, 37, 5, 63, 47, 66, 10] can be adapted to process these images to (i) detect and recognize the types of produce in the scene, (ii) recognize and associate pricing and other data from printed or handwritten display signs, and (iii) assess qualitative characteristics such as freshness and ripeness.

This will be achieved using an end-to-end produce detection and recognition pipeline. The pipeline will leverage state-of-the-art deep learning-based computer vision approaches to detect, identify and tag [37, 5, 66, 10] the fruits/vegetables in the image. Processing images captured in the wild increases complexity for these detection and recognition tasks: (i) robust scene text recognition [28, 63, 47] for recognizing structured and unstructured produce display signs, (ii) instance segmentation [66, 10] for identifying fruits/vegetables in produce displays in images, and (iii) algorithms for associating text labels from scene text recognition with produce image labels from instance detection. All pose interesting challenges for computer vision algorithms: Handling noisy recognition output and incorrect associations in particular is a challenge that we will address through UI design and by a novel uncertainty-aware data presentation pipeline discussed below.

Planning for Inclusive Technology to Strengthen Food Supply Networks in WNY

We intend to evaluate how information co-production (e.g., through REAP) improves information flow and strengthens food-related behavioral actions (e.g., purchasing, distribution, and consumption) among stakeholders within the food supply networks. The supply networks of the food system or the "middle infrastructure" involves a network of stakeholders that grow and build resilient food markets by connecting food production to consumption, leveraging credible information from multiple sources [12]. These supply networks work best when information is available and flows efficiently within the networks, such as location, quantity and quality of food produced. We will employ network (graph) analysis on data captured through REAP and supplemental surveys to examine how the availability and flow of co-produced information improves information flow and food-related behavioral actions between food suppliers and producers, suppliers and consumers, and producers and suppliers. A pre-survey of sample stakeholders within the food supply networks will be conducted before REAP is established to provide a baseline for the WNY FS. This survey will allow us to examine the structure and intensity of the networks among stakeholders using graph or network parameters such as density (level of food-related information types shared among stakeholders), weighted in-degree and out-degree (who is sharing specific food-related information types with whom), and eigenvector centrality (which stakeholders share different information types the most with others). Similar analysis (post-analysis) will be conducted after REAP is deployed; REAP provides an ideal platform for surveying users about the types of food-related information they access, who the information is shared with, and how the information types inform food purchasing, distribution, and consumption behaviours. We hypothesize that stakeholders within regional food

supply networks are more likely to share information to strengthen their food-related behavioral actions when food-related information is co-produced and easily accessible.

Presentation Techniques for Incomplete (e.g., Crowdsourced) Data
Data generated from crowdsourcing and machine learning is critical for the scalability of REAP. However such data may be missing fields, or contain inadvertent errors or ambiguities, and must be used with caution. For example, it may be difficult to distinguish apples and peaches in a fuzzy photo. Downstream consumers of this data should be made aware of these potential flaws: (i) Data displays (e.g., graphs) should communicate the potential for errors [6, 35, 58, 59], (ii) Data downloads should encode potential concerns in machine readable form, and (iii) Analyses and data transformations should track concerns [19, 21]. We will leverage the NSF-funded Vizier notebook (ACI-1640864) platform's ability to highlight and track data errors [21, 23, 7], instrumenting REAP's data ingestion processes to collect "uncertainty metadata" that will allow us to improve our existing approaches to uncertainty-aware data processing [19, 21].

Regional Inequities in the Food System by Race, Income, and Geography
A sustainable community data co-production program requires a process for setting objectives for data gathering and co-production. Our overarching goal is driving food equity, which exists when all people, regardless of identity, positionality, location, or power, have the right, ability, and opportunity to grow, procure, and/or consume healthful, affordable, and culturally preferred foods to lead a full life [54]. An equitable food system prioritizes equitable access to land, fair prices and wages, human health, and ecological sustainability. Movement toward food equity requires elimination of systemic barriers within the food system [2, 4, 27, 46]. Failure to document food assets (and challenges) at the regional scale masks racial and economic inequities between cities and surrounding suburbs, and suburbs and more rural regions. Thus, regional-scale solutions for equity (e.g., connecting rural growers with urban retailers) are overlooked. REAP will allow us to examine how food systems are serving people of varied demographic groups from multiple (i.e., spanning from urban to rural) regions. Variants of this question have been studied with coarse data for either rural areas or urban areas, but not for both communities within a region. We will use previously [53] tested spatial analyses, including spatial regression (logistic models) and Lorenz curves, to document inequities, by race and income, within and between urban and rural regions.

Project Team

This proposal brings together 6 academic faculty from varied disciplines and 4 community-based partners and investigators that span public and private sectors in the food system, and urban and rural regions in WNY. Faculty are Oliver Kennedy (Center for Analytics Research and Applications at UB), Samina Raja (Food Systems Planning and Healthy Communities Lab at UB), Debabrata Talukdar (UB School of Management), Srirangaraj Setlur (Center of Excellence for Document Analysis and Recognition at UB), Emmanuel Frimpong Boamah (Community for Global Health Equity and Department of Urban and Regional Planning), and Sara Behdad (Dept. of Environmental Engineering Sciences at UF). Community-based partners and investigators are: Allison DeHonney (Chair of Food Policy Council of Buffalo and Erie County and founder and CEO of Urban Fruits and Veggies), Kimberly LaMendola (Food Systems Manager, Southern Tier West), and Patrick Gooch (Senior Planner, Monroe County Department of Planning and Economic Development). Elizabeth Gosch will act as liaison to RFSI (see attached letter of support). Finally, a software developer will be hired to develop REAP under the guidance of PIs Kennedy and Setlur.

Community Engagement

The proposed project will work in parallel to a region-wide planning process to rebuild WNY's food system in response to COVID 19 called the WNY Regional Food Systems Initiative (WNY RFSI).

RFSI, led by a coalition of community organizations and facilitated by Ms. Elizabeth Gosch (see support letter), aims to develop a regional food system plan for nine counties. Our project team is already working closely with RFSI to develop an information portal that meets the needs of the region. If funded, we will establish an advisory group of RFSI planning process members who represent different sectors of the region's food system to guide the types of information collected by REAP and the paths by which this information will flow back to the community. The team will also conduct three workshops over the course of the planning project, a scoping workshop, an interim review workshop, and a final workshop to clarify goals for a full IRG proposal.

Intellectual Merit

REAP directly facilitates research on topics like: (i) understanding spatial patterns in how well the food system serves different parts of the region, (ii) understanding the market dynamics within the food system, and (iii) understanding how to facilitate community-led policy changes. Building REAP will also create research opportunities for research in computer science, ranging from image recognition (methods for processing scene text and subjective attributes like product quality) and incomplete data management (presentation and analysis of crowdsourced data). Finally, REAP will also provide a research hub, driving inter-disciplinary research questions by providing a repository of co-produced data and a platform for deploying new data co-production projects.

Prior Experience

The team has diverse disciplinary and sectoral experience in engineering, urban planning, and policy. Team members have co-produced action-research on food systems planning with community and policy partners (Raja, Frimpong Boamah, Kim La Mendola); published traditional research relevant to this project in their own fields of industrial engineering and environmental systems (Behdad), networks and game theory (Frimpong Boamah), data management (Kennedy), food systems planning planning (Raja), image recognition (Setlur), and markets (Talukdar); and led transformation in the food system through practice and policy (DeHonney, Gooch, and LaMendola). The results of this participatory action research generates new scholarship on food-systems planning [55, 48, 50, 51, 56, 57], form the basis of long-term policy change in the city and region,2 and serve as model for planning practice nationally [53, 42] and globally [51]. The UB Food Lab publishes policy briefs that summarize findings from traditional research articles and pressing food-systems issues in Buffalo and its surroundings [62], and worked with a metro-wide coalition to develop the One Region Forward sustainability plan, which includes a section on food [52].

Results From Prior NSF Support

PI Kennedy, Award ACI-1640864. $2.73 million, 1/1/2016-12/31/2020 (PI: Kennedy, Co-PIs: Glavic-IIT, Freire-NYU), "CIF21 DIBBs: EI: Vizier, Streamlined Data Curation." Intellectual Merit: This project explores techniques for managing messy data, and has produced 14 publications to-date. Broader Impacts: The publicly available Vizier system facilitates collaborative reproducible research between participants of varying skill levels. This grant funded one Ph.D. student, one developer, and has funded three undergraduate students.

PI Setlur, Award OAC-1640867. $2.91 million, 09/01/2016 - 08/31/2021 (PI: Govindaraju, Co-PIs: Rajan, Setlur, Furlani - all UB)."CIF21 DIBBs: EI: Data Laboratory for Materials Engineering." Intellectual Merit: This project has produced (i) A machine learning and informatics suite for large-scale data sets. (ii) Graphical ML workflow design UI for building prototypes for ML models. (iii) Data extraction tools for chart infographics. Broader Impacts: 21 conference and journal papers published, and multiple software packages released under open source licenses. The enhanced ChemML toolkit is widely used by material scientists. This grant is funding two postdocs (1 from an underrepresented group), five graduate students (1 female) and two undergraduate students.

PIs Raja, **Talukdar**, and **Frimpong Boamah** have not had NSF funding.

[12, 52, 53, 25, 36, 61, 49, 54, 65, 11, 26, 22, 2, 4, 27, 46, 55, 48, 50, 51, 56, 57, 42, 62, 18, 40, 41, 43, 45, 31, 32, 33, 34, 67, 8, 44, 9, 3, 60, 39, 24, 64, 30, 16, 14, 17, 20, 38, 15, 13, 28, 37, 5, 63, 47, 66, 10, 6, 35, 58, 59, 19, 21, 23, 7, 1]

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