Water On My Block: Reflections on Building A Participatory Artificial Intelligence System For Precision Weather With Scientists and An Urban Community

Kelly B. Wagman
Department of Computer Science
University of Chicago
Chicago, Illinois, USA
kbwagman@uchicago.edu

Kanchan Uday Naik
Department of Computer Science
University of Chicago
Chicago, Illinois, USA
kanchan@uchicago.edu

Madison Vanderbilt
Department of Computer Science
University of Chicago
Chicago, Illinois, USA
mmv773@uchicago.edu

Naeun Ko
Department of Computer Science
University of Chicago
Chicago, Illinois, USA
nbko@uchicago.edu

John Rugemalila
Department of Computer Science
University of Chicago
Chicago, Illinois, USA
johnruge@uchicago.edu

Thomas Chang
Department of Computer Science
University of Chicago
Chicago, Illinois, USA
tschang@uchicago.edu

Marshini Chetty
Department of Computer Science
University of Chicago
Chicago, Illinois, USA
marshini@uchicago.edu

Abstract

Creating accurate hyper-local climate Artificial Intelligence (AI) models requires neighborhood-level weather measurements and community partnerships. In this paper, we describe a three year case study of using a participatory approach to support the creation of hyper-local climate AI models, or what we term "precision weather." Using participatory design to involve stakeholders in the climate AI pipeline design process i.e., "participatory AI," we collaborated with a national laboratory and a community organization in a major metropolitan area in the United States, working with community members and scientists. We held interviews, co-design workshops ("Community Cafes"), and created an app for the community to collect flood reports in their neighborhood for advocacy and to contribute data to the AI model pipeline. We discuss our findings, lessons learned, and implications for future participatory projects to support hyper-local climate AI.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

urban, sustainability, weather, community, participatory AI, precision weather, hyper-local climate AI, climate AI

CHI '26, Barcelona, Spain

ACM ISBN 979-8-4007-2278-3/26/04
https://doi.org/10.1145/3772318.3790503

ACM Reference Format:
Kelly B. Wagman, Kanchan Uday Naik, Madison Vanderbilt, Naeun Ko, John Rugemalila, Thomas Chang, and Marshini Chetty. 2026. Water On My Block: Reflections on Building A Participatory Artificial Intelligence System For Precision Weather With Scientists and An Urban Community. In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26), April 13–17, 2026, Barcelona, Spain.* ACM, New York, NY, USA, 30 pages. https://doi.org/10.1145/3772318.3790503

1 Introduction

Climate Artificial Intelligence (AI) systems for cities often rely on coarse measurements to model weather at a city-scale, which makes it difficult to support neighborhood-level decision making in urban environments [16]. To better understand the impacts of microclimates in urban neighborhoods, climate scientists need hyper-local measurements of air quality, cloud coverage, precipitation, and heat levels. They can then use machine learning (ML) models with this data to fine-tune predictions and estimates to street level. These hyper-local climate AI models can serve urban communities, particularly those that are low-resourced, who often suffer the most severe consequences of extreme weather events such as flooding and heat islands. Providing data about climate impacts at the neighborhood level—as opposed to at a city level—can support efforts to secure resources for green infrastructure and minimize harms from extreme weather by clarifying who is affected and how. This data can also inform efforts to educate residents on precautions against flooding, extreme heat, snow, and poor air quality [47, 56, 75]. To support a mutually beneficial climate AI system, scientists and communities must work together to deploy measurement instruments, collect data, and make that data actionable for all stakeholders [18].

Using participatory approaches with local communities and scientists could create hyper-local climate AI models with community input and provide mutual benefit.

One approach to create a hyper-local climate AI pipeline that depends on neighborhood data is through "participatory AI." This approach refers to the process of using participatory design [9, 30], or involving people impacted by a system in the design process, for creating AI systems [7, 29, 48]. While participatory AI appears theoretically promising to support climate AI systems that benefit the communities they involve for measurements and observations, the definition is contested and little work exists on how to *practically* go about developing AI systems in a way that is mutually beneficial to AI system builders and the public [24]. Science-focused AI systems, in particular, increasingly involve the public, and the success of science relies on public trust in these systems. This is especially salient for weather AI systems because the forecasts and simulations they produce impact people's decisions about when to evacuate in an emergency, where to move, what kind of infrastructure to install, and more. Participatory AI could build trust in hyper-local climate AI systems by including those impacted by extreme weather events where weather measurement instruments are deployed in the design process. Some researchers do, however, caution that participation is not a panacea for improving ML and other AI systems and can also be potentially exploitative and extractive [68].

Yet, there is minimal prior work building real-world participatory AI systems in urban settings to see how and what forms of participation work well [10, 19, 33, 49, 74, 76] even though some have explored this concept theoretically in relation to climate data [54, 70]. In the Human-Computer Interaction (HCI) community, there has also been work on "climate services" [57] and tools for citizen science (e.g. [2, 35]) and a large body of work on sustainable HCI more generally (e.g., [5, 14, 28, 37, 59]). However, participatory design goes beyond the aims of citizen science or participatory urban sensing [18] because it is not just a way to collect data, but to ensure the system has tangible benefits for those impacted and that it centers those voices [19, 51]. Participatory design that "matters", i.e., design which shapes technology for a better society overall, needs to form strong engaged partnerships, build prototypes, focus on changes that avoid negative consequences for those impacted by technology, be rooted in technology, strive for democratic control of technology, and aim for long lasting impact [9]. This is a tall order for hyper-local climate AI projects, particularly since there are only a small number of research projects that have engaged in such processes.

In fact, most closely related to our own work is a project that created a participatory approach to deploying an air quality sensor network in Chicago to support hyper-local climate AI models in collaboration with the city, community stakeholders, and researchers [22]. They achieved success in enacting participatory design that "matters" [9] and developed a "three-legged" stool framework to describe how to do participatory design with the city, communities, and researchers. Our deeper dive into how one urban community and a set of climate scientists worked together over a period of three years to create a hyper-local climate AI partnership on flooding offers complimentary viewpoints to Daepp et al.'s [22] work around air quality. While we did not focus on local government in our target city (Chicago) as a stakeholder, we use this project as a case study to draw practical lessons about the efficacy and challenges of using a participatory approach to support hyper-local climate AI systems that make data *actionable* [21] in a real-world setting for one urban community.

Our research questions are as follows:

RQ1: How can community members in an urban neighborhood and scientists each benefit from a participatory approach to create hyper-local climate AI models and what are the challenges?

RQ2: What lessons can be learned about participatory AI and sustained community engagement to support hyper-local climate AI systems?

We approached these questions in a real-world setting where we collaborated with scientists at Argonne National Laboratory (ANL) in the United States (U.S.) who were developing hyper-local climate AI models and a community organization called the Greater Chatham Initiative (GCI). Both the scientists and the community organization were part of an existing initiative at ANL. The scientists have been studying climate and weather impacts in Chicago at a neighborhood scale (as opposed to city scale) which requires the deployment of weather measurement instruments in urban neighborhoods and partnering with communities to ensure the work is mutually beneficial. In this paper, we introduce the term "precision weather" to mean hyper-local climate AI models that leverage data from neighborhood weather measurement nodes and data about on the ground impacts. Precision weather requires a scientific approach that relies on localized data and machine learning to model weather conditions in a specific geographic area, for example, using AI to estimate the depth of flooding on a street from a camera image or to simulate how adding trees to a neighborhood would impact air temperature. While models can go far with these estimates, they also require labeled ground truth data on hyper-local, real-world weather impacts to fine-tune the models. This requires "bringing the people back in" in a more literal sense for dataset creation [25].

Our project had two goals: (1) to understand residents' and scientists' perspectives on building hyper-local climate AI models with community partners including how residents view data collection and its benefits, how scientists see community contributions, and what challenges arise in practice; and (2) to co-design a prototype app to support the partnership for precision weather with both groups and derive lessons from the process. In this paper, we focus on how we used participatory AI to engage and further develop the scientist-community partnership rather than the hyper-local climate AI models themselves. In particular, we sought to explore questions around the four parameters of participation in participatory AI outlined by Delgado et al. [24] including (1) *why participation is needed* from a community and scientists in hyper-local climate AI modeling, (2) *what is on the table* or determine what roles a community and scientists can play in hyper-local climate AI modeling, (3) *who should be involved* in these participatory processes, and (4) *what forms participation can take*. We were also interested in exploring Delgado et al.'s [24] four modes of participation, that is whether to merely *consult*, *include*, *collaborate with*, or provide true *ownership* over the hyper-local climate AI pipeline design process

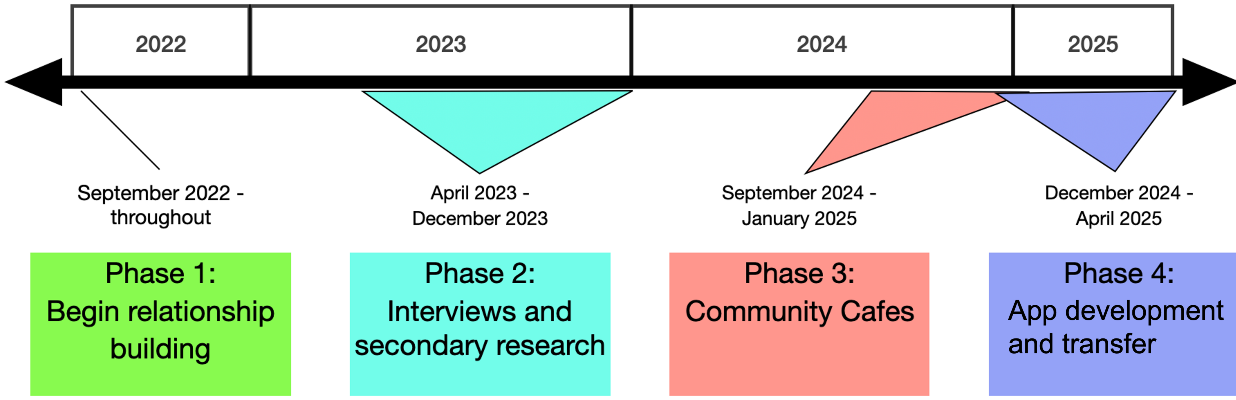


Figure 1: Timeline for project, include the four phases: relationship building, interviews, Community Cafes, and development and transfer.

for stakeholders, given that only few participatory AI projects they reviewed achieve the last mode of participation.

To achieve our goals on these lines of inquiry, we conducted four phases of research as shown in Figure 1. Phase 1 focused on relationship building and participant observation, including 30+ meetings and 3 in-person science and community events. Phase 2 involved interviews with 12 scientists and 3 community engagement specialists. Phase 3 consisted of three "Community Cafes" (N=62) where Chatham residents participated in co-design workshops to prototype an app to support hyper-local climate AI modeling and community data gathering efforts on weather impacts to improve decision-making around green infrastructure and responses to severe weather events. In Phase 4, we developed the *Water On My Block* prototype for flood reporting, designed to benefit residents and feed into the hyper-local climate science AI data pipeline.[1] Our paper focuses on the process of engaging in a participatory process and the creation of an artifact that represents scientists and community members shared goals for precision weather that benefit both groups rather than treating the tool as the sole outcome.

By centering both scientists' and Chatham residents' needs, our case study illustrates how participatory AI goals can align through the flood reporting tool. Residents use it to report flooding, access local incident information, and petition the city for resources, while scientists gain on the ground impact data to improve hyper-local climate AI models and simulations.

We have four major findings. First, hyper-local climate AI models for precision weather need to be actionable for impacted communities and achieving this impact is what communities find valuable more so than the fact that AI was used. Second, gathering ground truth data on weather impacts to input into hyper-local climate models from communities necessitates a translation mechanism that aligns the data requirements of scientists with what communities are able and willing to contribute—and vice versa. Third, differing stakeholder viewpoints of hyper-local climate AI models can impact what feasible artifacts can be created to enable a truly participatory AI pipeline from communities to scientists and vice versa. Finally, creating a shared artifact to represent scientists' and community members' goals for precision weather emphasizes the need for clarity around ongoing engagement, data ownership and governance, and privacy-preserving collaboration.

Our work has two main contributions: First, we contribute lessons learned for involving communities as data partners using a participatory approach for infrastructure building to support precision weather and hyper-local climate AI models, by centering their voices using what we call a Community Cafe model. This model is useful for engaging communities in participatory design for AI systems as others have called for [19, 51] but does not address challenges around equalizing power asymmetries, addressing funding challenges, or helping to determine which parts of an AI pipeline a community should contribute to or how. Our work provides a useful case study in the work and time it takes to get to equitable urban solutions from co-design between HCI researchers and community partners [22]. Second, we contribute practical insights from our case study of sustained community engagement for HCI researchers, scientists, companies, government, and non-profits to approach the development of AI systems in a way that builds community trust through participatory processes since so few case studies of this nature exist as noted by prior researchers [24, 70].

2 Related Work

In this section, we discuss how weather services emerged in the United States, as well as research on participatory AI and citizen science more broadly.

2.1 From Weather Media To Climate Services

In the U.S., the Weather Bureau was initially established in 1870 as part of the Department of War [67, 72]. Modern weather forecasting began in the early 1900's, and while the first computer forecast was completed in 1950, computer forecasting only began to be remotely accurate in the mid-1960's [67]. The Weather Bureau evolved, eventually morphing into the National Weather Service in the 1970's and is currently housed in the Department of Commerce [67, 72]. The

[1]The app was launched and used in the community subsequently but that evaluation is beyond the scope of this paper.

National Weather Service makes all of its data available to the public and issues forecasts. However, for-profit weather services such as AccuWeather and the Weather Channel compete with the National Weather service while using its data, and can display forecasts that are less accurate because of misaligned business incentives [67]. For example, a company may exaggerate a chance of rain because people can become upset with the service if, when there is a low chance of rain, they choose not to bring an umbrella, and then it rains. Instead, the company would prefer that people bring an umbrella and it turns out there is no rain. These companies are also not liable for being inaccurate unlike the federal government who will face backlash if disaster strikes owing to inaccurate national weather forecasts and warnings. The U.S. also runs the Hurricane Center, which is focused on forecasting hurricanes [67]. At the time of this writing, the administration is reworking numerous federal agencies and thus these services may not be available in the same capacity [11].

Media and communication researcher Marita Sturken coined term "weather media" to describe the spread of weather-related content, first on television and subsequently on the internet [72]. She explains that the Weather Channel was created in 1982 as the first 24-hour channel devoted to weather-related news. As Sturken points out, the Weather Channel's focus on near-term forecasting and prediction meant that longer-term climate trends such as drought were rarely discussed [72, 73]. Sturken describes the increasingly technologically-situated weather reports—such as deploying satellite imagery—as building on a human desire to control the weather via technology. The fact that the weather is ultimately uncontrollable makes it a site of fascination for many.

The proliferation of mobile phones, social media, and urban sensor networks have led to new kinds of weather media and personalized weather reporting. This has made it a rich area of study for HCI. Sustainable HCI (SHCI) has been a sub-field of HCI since approximately 2007 [5, 14, 66]. Bremer, Knowles, and Friday examined papers over a 15 year period to establish trends in SHCI discourse [14], finding that early work focused on individual behavior change that was later critiqued as being less effective than structural change such as policy intervention. This review paper argues that HCI researchers should use their expertise as designers and engineers to work on "green policy informatics." One example of green policy informatics includes a project that rigged stormwater sewers in Detroit with sensors and developed an AI system to manage and automate the flow of water [65]. Other examples include a tool that was created for complex digital services, such as Netflix and other companies, to measure their carbon footprint [64], and a project to instrument Chicago with air quality sensors and provide QR codes at bus stops so people could view the data [22]. Building on the idea of green policy informatics, other HCI researchers have called for more work on "climate services." Rigby and Preist [57] define climate services as *"the systems that provide climate, weather, and other related information to various stakeholders around to world to inform decision making processes, allowing for planning and preparation for upcoming conditions."* These authors show a lack of work in HCI on climate services, and the numerous possibilities that exist for important contributions [57]. We also note that there is a vast body of transdisciplinary literature on co-production approaches from the climate information and climate services domains that is well aligned with using participatory approaches to support climate AI[2]. These co-production approaches focus on how the creation and shaping of science knowledge around climate issues is culturally and socially situated and necessitates including stakeholders such as communities, non-profits, the private sector, and regulators to co-produce climate solutions [15, 41–43]. However, they are less focused on deeply understanding how and which participatory approaches can help support the design and evaluation of climate services or how communities perceive potential hyper-local climate AI solutions. Our project compliments these works and is situated within this history of weather media and climate services, approaching these topics from an HCI and design perspective.

2.2 Participatory Artificial Intelligence

In an effort to make AI systems beneficial and inclusive, scholars have turned to the long history of participatory design methods. The origins of participatory design trace back to Scandinavia in the 1970s and 1980s, emerging from labor movements that sought to involve workers in the design of workplace technologies [30, 45, 50]. Broadly, participatory design is a methodology that actively involves stakeholders—particularly end users—in the design process to ensure that the final product meets their needs and values [8]. Participatory design began in a political context to improve power relations between workers and system creators and continues to have an activist bent. Central to the idea of participatory design is that people are design partners, rather than merely participants, and that co-creation of prototypes is an important technique for facilitating this process [8]. In HCI, participatory design is a widely used technique [8, 26, 54] but many still debate questions around what participation means, who should participate and how, how projects should be run, and how to deal with questions of the scale around today's technologies reach [4, 77]. Recently, scholars building on the extensive participatory design literature have noted a "participatory turn" in the design of AI systems [24] as technology designers grapple with how to make these systems beneficial.

Like participatory design, participatory AI uses methodological techniques to include the people impacted by AI in its development—the main difference is that this is participatory design in service of AI systems. This is important because AI systems rely heavily on data for ensuring fairness, robustness, improving performance, and achieving reliability and often this entails data work by humans such as labeling data and contributing and creating datasets that is often overlooked or undervalued [38, 63]. Moreover, AI systems ultimately can impact human livelihoods through applications from science to healthcare and beyond. However, while numerous researchers have suggested participatory AI as a mechanism for making AI/ML more equitable, inclusive, robust, responsible, and trustworthy, there is no consensus on how to do this in practice [6, 19, 24, 39, 51]. Delgado et al. provide a review of participatory AI practices found across 56 research papers and suggest a framework for precisely describing participation goals or why participation is needed, who is participating and what they have influence over (or participation scope), and what form this participation takes (or

[2] A full discussion of these approaches is beyond the scope of this paper.

participation form) [24]. They also define four dimensions of participation: consult (where stakeholders rank preferences for policies in a design in a ranking), include (where stakeholders can deliberate about policy/design options), collaborate (where stakeholders co-create designs or policies), and own (where stakeholders own the design or policy processes). By sorting papers into these categories of participation, they find that very few papers provide true ownership to the stakeholders involved in the participatory AI design process. In addition, some researchers have warned that involving impacted communities in ways that are performative or even exploitative could cause more harm than good [6, 19, 23, 51, 68]. Participatory AI can be particularly fraught when stakeholders are from diverse backgrounds and have differing needs [23].

While there are concerns about participatory AI, there are also a handful of examples of projects that have benefited communities. For instance, the organization *Queer in AI* has orchestrated a number of initiatives to improve the participation of queer people and perspectives in the design and development of AI systems [55]. In another example, Suresh et al. [74] point out that *"there are not yet examples of how to apply feminist and participatory methodologies from the start... [to] design machine learning-based tools"* and they describe their project that involved co-designing datasets and ML models in partnership with activists working on femicide. While not all explicitly focused on AI, we also draw on work by Erete and others who contend that community-based technology design should augment social cohesion, engage small groups within a community, and reflect the interests of the community to encourage participation [19, 20, 32, 40, 51]. In this project, we build on this history of participatory design and contribute practical lessons from a case study of using participatory approaches to engage scientists and an urban community to support hyper-local climate AI.

2.3 Citizen Science

Our project is informed by prior work on crowdsourced scientific data and citizen science. A citizen science paradigm typically involves non-scientists collecting data and either donating this to existing scientific efforts or using it for their own purposes. Previous work in HCI on citizen science has looked at informatics tools needed to support citizen science [2, 52, 53], technologies for encouraging participation/motivation in citizen science efforts [3, 36, 37, 60], ways of visualizing science information for non-experts [69], and privacy considerations when collecting citizen science data [12].

One exemplary paper looks at a citizen science online community called *Weather-it* [2]. The paper argues that *Weather-it* is a form of "citizen inquiry" rather than citizen science because the online community allows users to develop and carry out their own investigations of weather and share these outputs with others (as opposed to collecting and donating the data to science). In fact, their research finds that while in citizen science projects participants often list contributing to science as a core motivation, *Weather-it* participants were mainly motivated by an interest in the topic of weather.

In another example, Jennifer Gabrys spent years studying air pollution-focused citizen science projects [35]. A core barrier she identified for citizen science projects is that when activist groups take this data as evidence to e.g. a government body to advocate for change, the government body can dismiss the data as not sufficiently scientific and thus not believable. Gabrys also explains that even well-collected data does not necessarily translate into action for citizens—it takes significant effort to make this a reality. Related to citizen science, some researchers have also explored trust in digital civics more generally [20], ecologies of participation in general [58], and how politics affect HCI research in community-led research [27].

While our project builds on ideas from citizen science, our work is not citizen science per se because its goal is to be bi-directional. By that we mean that while citizen science implies a single directional flow of information (from participants to science), this project is also concerned with the flow of information from science to residents and ways that this information can directly benefit residents.

3 Methods - Phases 1-3

We partnered with ANL and GCI and undertook four phases of research as summarized in Table 1 to answer our research questions. Our research team consisted of one graduate student, five undergraduate students, and one faculty member. All of our work was Institutional Review Board (IRB) approved.

3.1 Research Context

Our work built upon a project that created an air quality sensor network in a major city with city officials, community stakeholders, and residents who called for deeper set community engagements such as co-design workshops to create equitable urban sensing networks [18, 22]. Their project did not focus on AI and relied on the city as a pillar for participation. In contrast, we focus on the relationship between scientists and residents and how an AI system can impact residents, beyond simply broadening access to sensors and sensor data. In our work, we collaborated with an ANL initiative, that is, an urban integrated field laboratory where scientists are deploying approximately 21 multi-sensor instruments around Chicago to measure weather and weather impacts at a hyper-local scale. Weather has traditionally been measured at a city scale, often with a single weather station for an entire city or town. The initiative aims to shift this paradigm by collecting neighborhood-specific weather measurements (e.g. temperature, air quality, cloud cover, humidity, wind speed and direction, precipitation etc.) and weather *impact* measurements (e.g., using machine learning to extract the depth of water on a street from image data). To collect measurements, climate scientists are deploying multi-sensor instruments that use edge computing and AI to record weather conditions and transmit data back to researchers at regular time intervals. The data is then fed into climate AI models to provide hyper-local information that can allow specific neighborhoods to determine how to understand the potential impacts of extreme weather events as well as how to mitigate them. This is a different approach to traditional climate modeling which is constrained by not having enough measurement instruments deployed at the neighborhood level to accurately model or 'downscale' predictions to a level that is of more direct use to specific urban communities, rather than at the city or town level. The resulting hyper-local climate AI models can reveal how atmospheric and terrestrial systems shape heat islands,

Phase	Type of Data Collected	Participants
Phase 1 - Relationship Building	Observation, Field Notes	30+ Scientist/Community Org Meetings
Phase 2 - Interviews	Interviews	15 Scientists and Community Members
Phase 3 - Community Cafe 1	Surveys, Storyboards, Field Notes	21 Community Members
Phase 3 - Community Cafe 2	Surveys, Mockup Annotations, Field Notes	27 Community Members
Phase 3 - Community Cafe 3	Surveys, Prototype Evaluation, Field Notes	14 Community Members
Phase 4 - App Development	No formal data collection about deployment	N/A

Table 1: Summary of Data Collection

flooding and other stresses affecting residents, businesses, and the local environment.

The output from the scientists' work on the precision weather initiative includes raw data, accessible using a Python API, and computational models of neighborhoods. This initiative has partnered with local community organizations in Chicago including GCI which is focused on driving economic growth in the Chatham neighborhood. 94% of Chatham residents identify as Black and Chatham's median household income is $39,348 [34]. Chatham has a long cultural history and GCI was born from a comprehensive plan for neighborhood vitality.

We developed a collaboration with the ANL team and GCI to bridge the gap between the scientists and community residents such that residents could benefit from and participate in the precision weather system. Throughout the project the ANL team and GCI were working towards deploying a weather measurement instrument in Chatham and were regularly engaging to ensure communities members could learn about hyper-local climate AI modeling, the resulting data, and the measurement instruments.

3.2 Phase 1: Relationship Building and Participant Observation

Prior to beginning formal data collection, we spent considerable time building relationships with science and community stakeholders. We conducted participant observation by attending 30+ virtual science research meetings as well as community organization events, documenting with field notes (beginning September 2022). Events included an in-person event celebrating a scientific measurement instrument deployment, a flooding-focused community-organized event where we did a 30-45 minute presentation and discussion, and an in-person conference bringing together scientists and community members. We also held discussions with community and science leaders and presented storyboards of various scenarios of what we could build for the community using precision weather AI data. Examples included a *Data Ambassador* program for people in the community to learn about scientific data and build apps for their communities, as well as apps to collect data on flooding in the community (see Figures 2 and 3). Community and science leaders provided feedback and contributed envisioned scenarios of uses for the scientific data. We also reviewed community organization websites and followed the scientists' main Slack channel. Phase 1 allowed us to develop trust with each stakeholder group, learn broadly about their interests and priorities, and show our commitment to longer-term engagement.

3.3 Phase 2: Semi-Structured Interviews

In Phase 2, we conducted 15 one-on-one semi-structured interviews with scientists, community members, and community engagement strategists between April 2023 and December 2023. Interviews lasted 30-45 minutes and were conducted virtually over Zoom and recorded. We recruited participants by reaching out directly to members of the ANL initiative via email and Slack, as well as ANL partners. Participants were compensated with $25 Amazon gift cards. The full interview protocols are in Appendix A.1 and Appendix A.3. In addition, all participants completed a demographic survey (see Appendix A.2).

We used interviews to understand stakeholder goals for the ANL initiative and broader hyper-local climate AI goals. We asked scientists about their perspective on community involvement in developing and consuming climate AI models and we asked community engagement specialists how they thought community residents might get involved.

Interview participants were predominantly scientists and included both researchers and software engineers. Participants working on the science side were mostly white men with doctoral degrees between the ages of 25 and 44, which is representative of the ANL population. Community engagement specialists identified as Black or African American women, and all had a long history of working with communities in the Chicago area on a variety of projects. See Table 2 for the full list of participants.

3.4 Phase 3: Community Cafes

Once we analyzed our interviews, we conducted three "Community Cafe" events with Chatham residents in collaboration with our nonprofit community partner. Community Cafes are a method used by GCI to engage residents during an in-person discussion-based event, and they build on the World Cafe model [17]. Aspects of the World Cafe method include: a welcoming environment, small group discussions at tables, and providing food to participants. We compensated participants with a $25 Amazon gift card for the in-person event and $15 for completing any surveys sent prior to or completed at each event. All events were held in-person in Chatham at either the GCI headquarters or a community center. Participants were recruited by our community partner via their email listserv. We did not audio record the discussions and instead had each facilitator in the research team take extensive field notes and photos. Where possible, in-person participants and online survey participants completed a demographic survey[3]. The research team also engaged in

[3]We note here that gathering demographic data at community events proved challenging. Some participants only wanted to complete a form online from their mobile phone while some (especially the older adults) preferred to use paper surveys. We aimed to

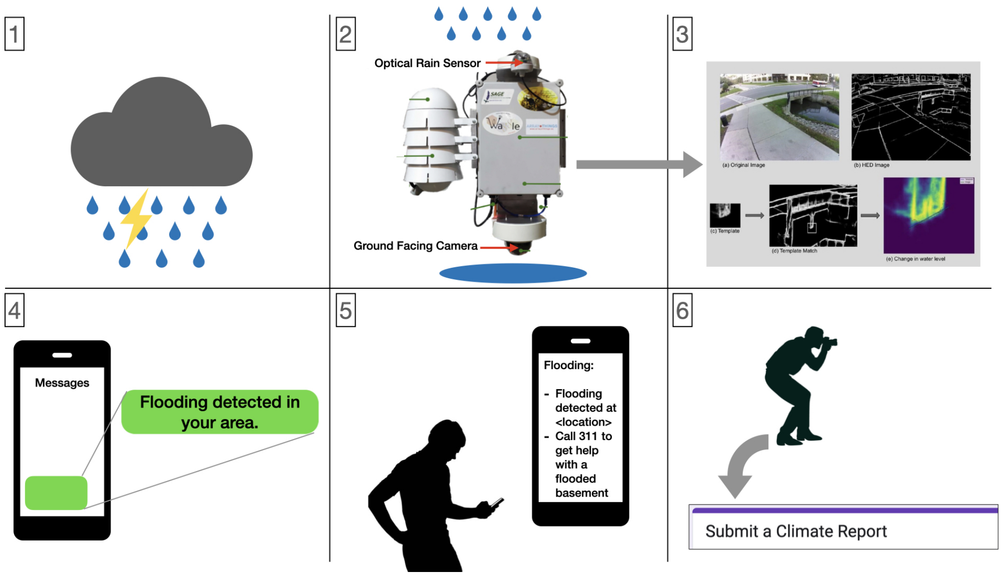


Figure 2: One of several original storyboards shown to community partner representing a flood alert text system.

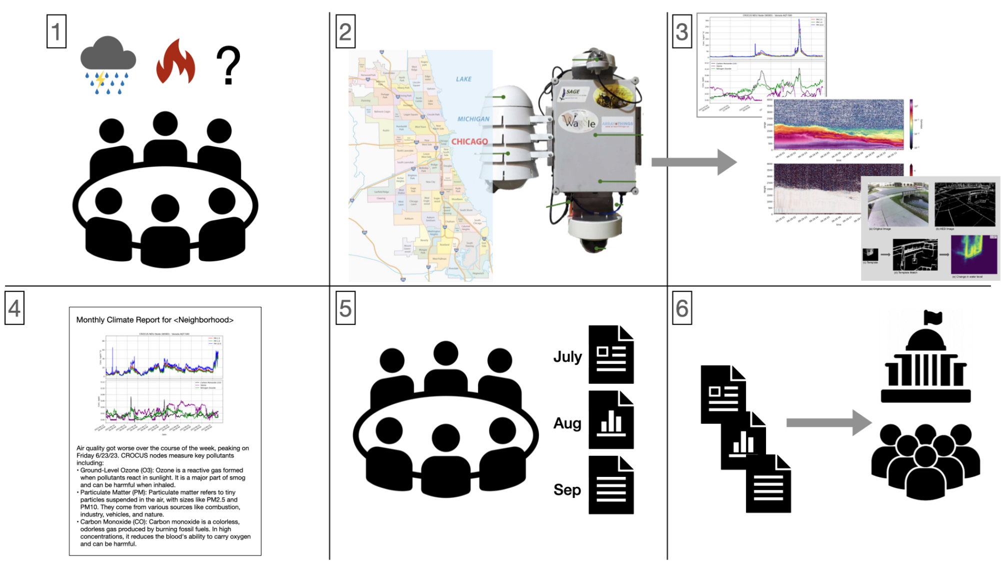


Figure 3: One of several original storyboards shown to community partner representing community reporting and data advocacy to local governments.

a team debrief after each Cafe for data collection and analysis purposes. We note that we had good continuity in participation across the three events with 11 participants attending at least two events (e.g., most commonly Community Cafe 1 and Community Cafe 2, or Community Cafe 1 and Community Cafe 3) and one attending all three events[4]. Overall, we had 48 unique participants across the cafes.

Community Cafe 1. was held in September 2024, lasted three hours, and had 21 in-person participants. In this first event, we focused on understanding Chatham's weather concerns broadly, and how residents thought technology might support or address these concerns. We led discussions with questions such as *What*

be accommodating of all preferred modalities but even so, not everyone turned in a complete form in either modality.

[4]In Community Cafe 2, seven participants attended from a prior event. In Community Cafe 3, seven participants attended from a prior event.

Table 2: Interview Participant Demographics
*Number of years in research after terminal degree.

ID	Gender	Age	Race/Ethnicity	Education	Occupation	Years in research*
P1	M	45-54	White	Doctoral degree	Atmospheric Scientist	25
P2	M	25-34	White	Master's degree	Research Software Developer	2
P3	M	25-34	White	Master's degree	Atmospheric Scientist	3.5
P4	M	25-34	White	Master's degree	Research Software Developer	7
P5	F	35-44	White	Doctoral degree	Atmospheric Scientist	8
P6	M	35-44	Middle Eastern or North African	Master's degree	Research Software Developer	7
P7	F	35-44	Asian	Doctoral degree	Computer Scientist	5
P8	M	35-44	Hispanic, Latino, or Spanish origin	Doctoral degree	Computer Scientist	3
P9	M	35-44	Asian	Doctoral degree	Atmospheric Scientist	10
P10	M	35-44	White	Doctoral degree	Atmospheric Scientist	7
P11	M	35-44	Asian	Doctoral degree	Computer Scientist	4
P12	M	55-64	White	Doctoral degree	Atmospheric Scientist	32
P13	F	45-54	Black or African American	Master's degree	Community Engagement Specialist	N/A
P14	F	65-74	Black or African American	Master's degree	Community Engagement Specialist	N/A
P15	F	55-64	Black or African American	Bachelor's degree	Community Engagement Specialist	N/A

are some examples of times when a weather issue was a problem for you? and had participants draw a storyboard for a new app in a weather scenario of their choosing. See an example of storyboards in Figure 4. The full facilitator guide is in Appendix A.6 In addition to discussions, participants completed a survey about their main weather concerns and demographic information (see Appendix A.4).

Community Cafe 1 Participants: We only received 17 demographic surveys for Community Cafe 1 from in-person survey participants. 14 participants were female and three were male. Two participants were 35-44, three were 45-54, two were 55-64 and nine were 65-74. One participant had a high school degree, seven had an associate degree[5] or some college[6], four had a bachelor's, and five had a master's degree. Eight participants rented and nine owned their homes. 13 had experienced flooding in their homes, 12 in the street, and three reported flooding in an office, outside basement or on commercial property.

Community Cafe 2. was held in October 2024, lasted 45 minutes, and had 27 in-person participants. It focused on refining what a precision weather app should do and how people should interact with it, building on findings from Community Cafe 1. We provided three possible mock-up app designs to participants who voted and provided feedback on these designs as shown in Figure 5 (see also Appendix A.7 and A.8). We emphasized that the final design could combine different aspects of each mock-up. The first mock-up was for a system that would send text messages about air quality and allow users to text back to develop personalized AQI (Air Quality Index) thresholds for poor air quality; the second mock-up was a web app for reporting local flooding incidents; the third mock-up was a website with neighborhood-specific weather resources. Participants also annotated paper versions of the mock-ups to provide feedback and filled out a survey which included voting on their favorite mock-up. We also held a Zoom call with the scientists' team to gather feedback on the mockups.

[5]An associate degree is an undergraduate degree lasting two to three years. It is considered above a high school diploma but below a bachelor's degree in terms of academic qualifications.
[6]Typically, this could mean a participant began an undergraduate or "college" degree but did not complete it.

Community Cafe 2 Participants: Of the completed demographic forms we received for Community Cafe 2's attendees (15 using an online form, 12 on paper), all participants reported being Black/African American with 21 females, 4 males and 2 declining to report. The majority of participants had bachelor's degrees (12), followed by high school (3), master's (4) or associates/some college (3), and two doctorates, one less than high school, and 2 declining to report. 18 owned their homes, six rented, and three did not specify. Ten participants were between 65-74, seven were 45-54, three were 35-44, four were 55-64, and one was over 75 (Two did not specify). Occupations ranged from 11 retirees to social work, administration, comedy and consulting, and one unemployed participant. 17 participants had experienced flooding in their home and 10 had also experienced flooding in the street with only 1 participant stating they had not experienced flooding, and two declining to report. At least eleven participants had contacted their local representative about flooding (one declined to report) with nine feeling the result was somewhat helpful or very helpful. 20 participants had used 311 to make a report with 17 reporting it was very helpful or somewhat helpful.

Community Cafe 3. was held in February 2025, lasted three hours, and had 14 in-person participants. Based on feedback from the prior events, we built a prototype of a flood reporting web app and in this event, we focused on getting feedback on the prototype (see Figure 7). Participants tried the prototype live on our laptops and discussed usability and features as well as on privacy and data governance given the sensitive nature of user-generated flood reports. Participants also completed a paper survey to evaluate the prototype (see Appendix A.9).

Community Cafe 3 Participants: All participants were Black/African American, 10 were over the age of 55, two were between 35-44 and 2 were between 45-54. The majority of participants had an associate or some college degree (5) or a bachelor's (5). Three had a master's degree and one reported only having a high school diploma. Eight owned their homes and six rented. Only one had not experienced any issues with flooding, the majority experienced street flooding (11) and/or in their homes (8). Participants had a range of occupations from community health worker, school crossing guard, to retiree, construction, and singer.

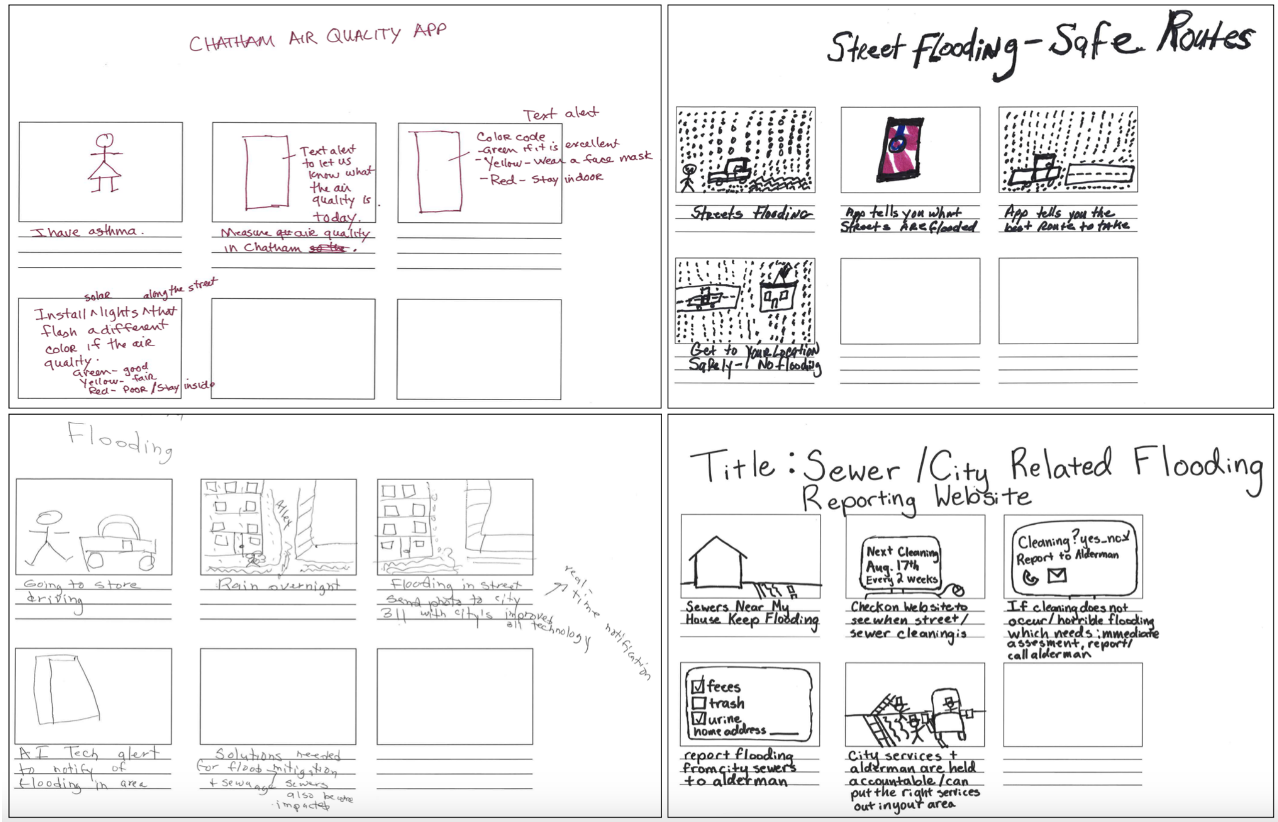


Figure 4: Storyboards created by participants in Community Cafe 1 showing how an app could support different weather scenarios.

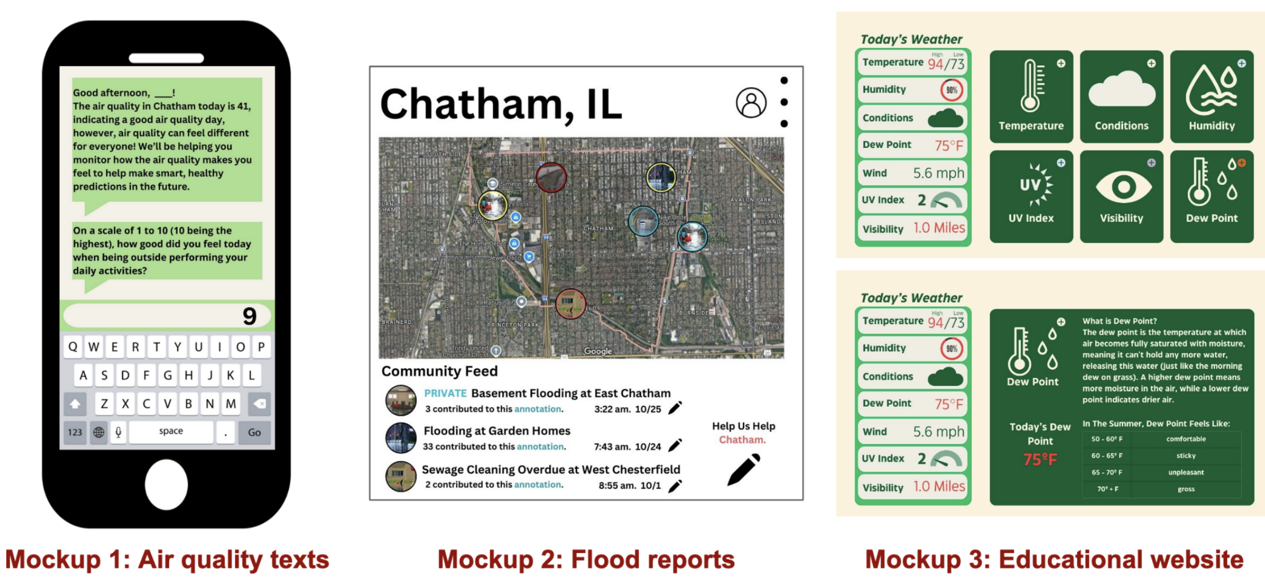


Figure 5: Mock-ups designed by our team presented to community residents during Community Cafe 2 for voting and feedback.

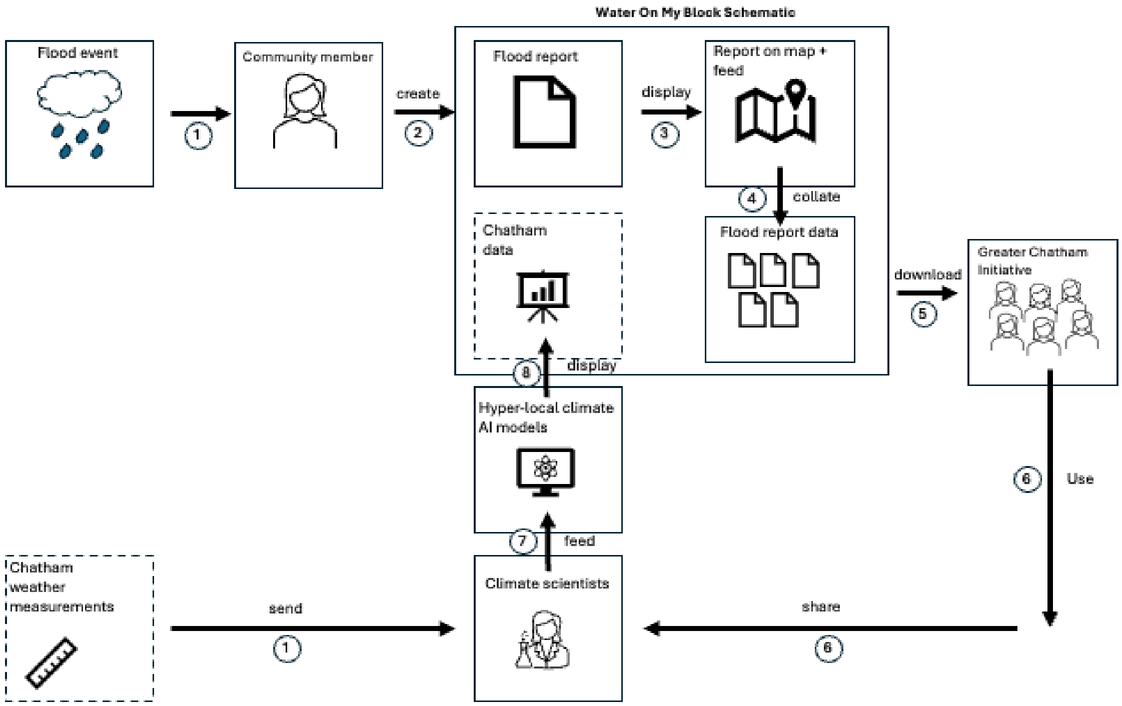


Figure 6: Schematic of *Water On My Block* showing how flood reporting data is submitted and seen by community members, the Greater Chatham Initiative (GCI) and Argonne National Laboratory (ANL) climate scientists. Dotted lines indicate parts of the system that were not yet implemented at the time of the study.

4 Methods - Phase 4

4.1 Phase 4: App Development and Transfer Of Ownership

We began developing the flood reporting app in December 2024 after analyzing data from the first two Community Cafes and the meeting with the scientists about the mockups. We evaluated an early prototype of the app in December-January 2025 with the GCI leaders and ANL scientists in a zoom call and evaluated our final prototype in Community Cafe 3. As we worked through the initial phases of our project, we also set an agreement with ANL and GCI that our formal research would conclude with the ownership transfer of the prototype to GCI after Community Cafe 3. We committed to and made all bug fixes and improvements based on Community Cafe 3 to support the deployment of the prototype beyond Community Cafe 3 to support a flooding data collection campaign led by ANL in collaboration with GCI in late March 2025. We were not involved in this final deployment as part of formal data collection and as such, the results of that launch are beyond the scope of this paper. We met with GCI in late June 2025 to complete the transfer of ownership of the *Water On My Block* prototype. This involved walking staff members from GCI through the structure of the app, talking through sustainability issues such as reviewing all costs involved in technologies used to run the app (e.g., for web hosting which we agreed to support through the end of the calendar year along with providing technical support during that time period), and how to download and use the data reports. We also talked through how the data could be shared with scientists and how to further incentivize use of the app. All partners and our team are also still in contact regarding the larger ongoing partnership between the lab and the nonprofit in Chatham.

4.2 Design Considerations For App to Support Precision Weather AI

4.2.1 Deciding to Build A Tool For Precision Weather. The first decision in our project was whether to build an app as part of the participatory AI process. Scientists told us that precision weather and the hyper-local climate AI models they were building required ground truth data on neighborhood-level weather impacts which could only be gathered from the community itself to supplement the data collected from their hyper-local instruments. For instance, they could get measurements on precipitation near their measurement nodes as frequently as every hour but they did not know when flooding occurred in the neighborhood. Knowing the impact data could help fine-tune hyper-local climate AI models. They were also supportive of an education program to help get community members familiar with the scientific data to build their own reporting mechanisms and apps out of this climate data. When we presented storyboard ideas to the community partner, they felt that the more socially-focused ideas such as the Data Ambassador program to help residents learn how to use the scientific data would not provide an immediate tangible benefit to the community. Instead, they felt an app would be a tangible and shareable way to convey the

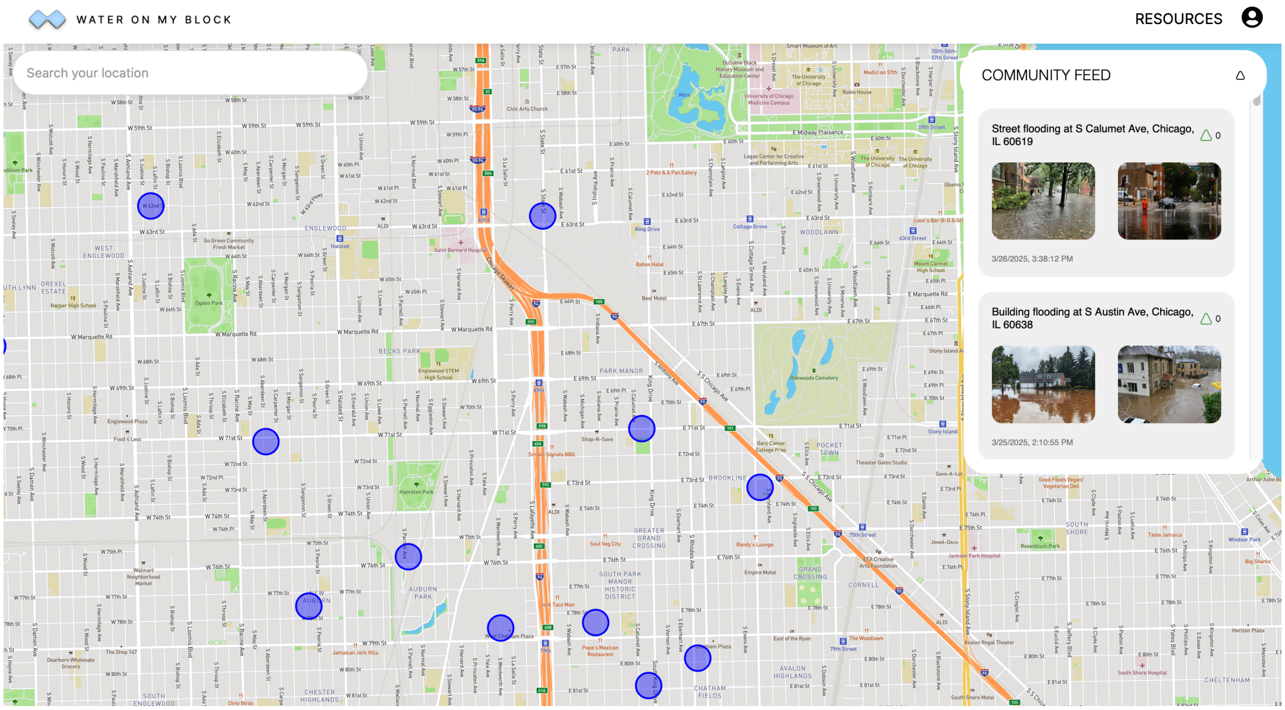


Figure 7: *Water On My Block* showing placement of map, community feed, and navigation to the Resources page (mock data points to demonstrate functionality).

importance of the climate science to more residents. We note here that in this case, we relied on the partner organization who had a deep understanding of community needs to make this decision on behalf of the community. Moreover, to avoid being exploitative and contacting community members directly for consulting on every decision, this form of participation was deemed the most favorable to safeguard and respect community members' time. Thus, given our skills as HCI researchers and the community's desire for a tangible product related to precision weather, that is gathering hyper-local measurements and weather impact data, we decided to build an app to benefit both scientists and community members to support the hyper-local climate AI pipeline they envisioned.

4.2.2 Focusing On Hyper-local Flood Reporting For Precision Weather Impacts. During the first Community Cafe, it became clear that urban flooding was the community's most pressing climate concern. Of the 19 storyboards created by participants, 14 focused on flooding, reinforcing its urgency across households and age groups. Key takeaways were that residents wanted to be able to track severe weather events and alert older adults or tech-averse neighbors about flooding or adverse events. In addition, residents felt that existing tools they used such as GroupMe[7] were useful for block-level updates on flooding, fires, and climate events but still lacked neighborhood-wide visibility. The second Community Cafe surveys reaffirmed flooding as the top climate concern (56% of participants), followed by health-related impacts such as mold allergies (41%) and mental health challenges (16%). Of the three prototypes presented, Mockup 2, the interactive map-based flood reporting tool, received the strongest support, with 55% of residents selecting it as their first-choice design. Residents also liked the educational resources in Mockup 3 on flood insurance and tree infrastructure. We combined these ideas into *Water On My Block*, which also drew design inspiration from a tool where users provide data on sidewalk accessibility [61]. At this point, our intention was also to integrate and visualize ANL's hyper-local climate AI modeling data from Chatham but the instrument was not deployed during the time of our project.

[7]https://groupme.com/

4.2.3 Reflecting On Data Privacy and Governance. Data privacy and governance were a top priority since the beginning of our participatory AI design process. In our initial feedback meeting with scientists over Zoom, we discussed data sovereignty as scientists felt that the non-profit should own the data but that the data needed to be in a format that was easy to share between stakeholder groups. This was echoed by GCI and the community engagement specialists we interviewed. We collectively decided that any data collected would be owned by our community partner and they would have sole discretion when deciding who to share the data with.

4.3 App Features

Our app focuses on collecting hyper-local flood impact reports from residents to supplement data from neighborhood-deployed measurement instruments. In future versions, the app could also display outputs from hyper-local climate AI models. These reports help the models better correlate measurements with on-the-ground impacts.

Since the scientists had not yet deployed their Chatham measurement instrument, the prototype could not be as tightly coupled with the scientific precision weather data. Future versions of the app could incorporate their Python libraries to include hyper-local climate AI data and data from the measurement instruments. The flow of information in the app is depicted in Figure 6. As seen in this figure, (1) when a flooding event occurs in Chatham, it is also measured by ANL's weather instrument. Using the app, a community member may decide to (2) create a flood report and this flood report (if public) is (3) displayed on a map of the neighborhood along with (optional) images and also in a community feed of recent flood reports in the neighborhood. Viewers can navigate the map to view current and recently past flooding incidents reported. Community members can also send reports to their local government officials using the app and they can also view resources around flooding in the app.

As shown in Figure 6, the raw flood report data that community members have submitted can be (4) collated and (5) downloaded by the neighborhood nonprofit who owns the data. They can then (6) use this data for advocacy efforts and decision-making around neighborhood improvements to mitigate flooding and/or (6) share the data with climate scientists at ANL. The climate scientists can view the data which is (1) sent back from their measurement instrument in Chatham at regular intervals after edge computing/AI cleans and aggregates the data. They can (7) feed the instrument data or the data from the app's flood reports into their climate AI models to model hyper-local trends related to flooding. The app can also (8) display the data from ANL's neighborhood instrument and precision weather models. ANL had deployed measurement nodes in two other neighborhoods over the first two years we worked on the project and they had hyper-local climate AI models from those neighborhoods. During our project timeline, they were still working towards the Chatham deployment, which reflects the time and resources required to set up a fully functional hyper-local climate AI pipeline in each locale.

The mobile-optimized web app includes:

- **Map Interface:** An interactive map (Google Maps API) lets users click on a location to annotate it with a flood report. A fixed-radius marker appears with a form to describe the flooding events. Users can also search by landmark, building name, or general area to annotate their intended site.
- **Community Feed:** A chronological view of flood reports including timestamp, location category such as street or home, a brief description, and an optional image per report. Hovering over a report centers the map on its location and entries can be upvoted to allow residents to draw greater visibility to specific annotations, similar to what residents told us they can do in GroupMe chats.
- **Annotation Form:** Users are prompted to select the category of the flooding incident (e.g., "Street," "Sidewalk," or "Basement.") in a form that dynamically adjusts to ask only context-relevant questions. The form also presents discrete, labeled categories to capture structured data usable for scientific analysis. The form questions, co-designed with GCI and ANL, avoid technical jargon and guesswork (e.g., "Is the water clean or dirty?") and includes "I don't know" or "Other" options.
- **Resources Page:** This is a static information hub with local flood resources for Chatham including flood insurance, sump pump maintenance, tree infrastructure laws, and local green infrastructure efforts. A resident-facing FAQ explains how map data is collected, anonymized, and used. These reports can help hyper-local climate AI models better correlate measurements with on the ground impacts community requests for clarity around data privacy and access and links to our IRB consent form. There is also a public feedback form for bug reports and suggestions.
- **Advocacy:** To make the data actionable for advocacy, we included a link to auto-generate an email with the flood incident data for the alderman. We also include an optional link to report to 311 even though this was not always seen as useful by residents.

4.3.1 Implementation. The web app backend is powered by Node.js and Express.js (to be able to save data, check logins, and respond to user requests, and handle what to do when someone visits the website), with MongoDB, a database, managing all data storage for the app, including storing user-uploaded images. The frontend, or part of the app that users interact with, is built with React.js, and to enhance mapping features, the app uses Leaflet.js, a library to display maps and markers in a web app, alongside the Google Maps API (which can take a search query and display it on a map) for location searches. Axios facilitates communication between the frontend and backend parts of the web app. We use Google Firebase for user authentication (including passwords and account verification) for secure access and we deployed the app via Amazon EC2 (the virtual machine where the app runs on the Internet) for reliable hosting.

4.4 Data Analysis

All interviews were transcribed by Rev.com under a non-disclosure agreement. We qualitatively analyzed the interview transcripts using the software MAXQDA in two rounds using thematic analysis [13, 62]. First, we reviewed and familiarized ourselves with the data and developed an initial codebook as a team based on this review (inductively) and our interview protocol. Next, we did an initial coding of the data using the codebook in Table 3 following a deductive approach. After this stage, one member reviewed the coded data to search for themes and as part of this process, they developed subcodes for each top-level code. Then, a second member of the research team reviewed all the data again to do another round of subcoding, reviewing existing subcodes, and raising points of disagreement for discussion. For each top-level code that we determined corresponded to the main themes of the data as a team, one member of the research team developed a thematic summary of the code based on the subcodes. This involved creating a summary of each theme using extracts from the data to support the narrative. The research team then discussed and reviewed all the thematic summaries to derive the final themes in this paper. In this paper, we focus on the themes arising from the top-level codes bolded in Table 3. These themes include what roles scientists envision for communities in an AI pipeline, what precision weather AI means from a

Table 3: Codebook for Interviews

Code	Code Description
Individual goals	Individual goals each interviewee has for their own work
Argonne National Laboratory goals	Perspective on broader goals of Argonne National Laboratory
Weather concerns	Interviewee's broad Weather concerns
How Argonne National Laboratory can contribute	Views on Argonne National Laboratory contributions to community partners
How community can contribute	Perspective on what communities can do to help with
Stakeholders	Views on stakeholders interested in Argonne National Laboratory data
Perceived gaps	Perceptions of gaps between scientists/communities
Weather actions outside work	Weather actions interviewees have taken outside work

community perspective, and challenges to achieving community based weather AI.

We also conducted a similar process of thematic analysis on the participant observation field notes, open-ended responses from the surveys from the Community Cafes, and sketches and annotated mockups from the Community Cafes. After each Community Cafe, two members of the research team qualitatively coded hand-written sketches, feedback in survey open-ended responses, and field notes using MAXQDA. We then summarized these codes into themes to guide design decisions throughout the project through team discussions to reach consensus. We also calculated descriptive statistics on the closed-ended survey responses. Finally, the entire team discussed these thematic summaries to derive the final set of findings reported in this paper. The main theme arising from this analysis was around the pros and cons of a precision weather AI artifact for scientists and communities. Note, our data does not lend itself to deep comparisons based on age, gender, education, and race and as such, we do not touch on those issues until the discussion section.

5 Findings Phases 1–3: Understanding Community and Scientist Needs and Challenges for Participatory Weather AI

We first report findings from the first goal of the project to understand the needs and perspectives that both scientists and community members had with respect to hyper-local climate AI systems for precision weather.

5.1 How Scientists Envision Community Could Participate in AI Pipeline

First, we describe how scientists envisioned community members could contribute labeled ground truth data on weather impacts (such as air quality and flooding) and insight that would shape the hyper-local climate AI models simulating their neighborhoods for precision weather. Scientists differed, however, on what type of data they thought would be most useful, how it could be collected, and how it could be used in the AI system.

5.1.1 Types of Community-Sourced Data and Collecting Weather Impact Data For Precision Weather AI Models. Multiple scientists spoke about on-the-ground images of weather impacts as a useful form of data, ideally with categorical labels. Community-provided neighborhood images during weather events of interest could show both flood and snow depth that could be extracted using machine vision algorithms. Categorical weather labels overall were of interest, such as to describe current conditions as "icy" or "snowing." Scientists also said collecting geolocation was critical and that this needed to be at least as precise as a city block; for their purposes, a zip code would be too broad for precision weather and hyper-local climate AI models.

Yet, the question of how to collect community-sourced data on weather impacts was unclear. Scientists told us they had heard of meteorologists using social media to get real-time community data of weather impacts via hashtags. They also mentioned lower cost weather sensors that residents could place and monitor to help collect data for hyper-local climate AI models. Lastly, they said a dedicated app to collect information on weather impacts could work well for supplementing sensor data they could pick up and improving their hyper-local climate AI models. Scientists said it would be important to train residents on how to collect scientifically useful data, such as what a "good" photo would be or how to use the weather sensors if they were asked to place them at their homes.

5.1.2 How Community-Sourced Data Could be Used in AI Models (Or Not). Scientists also had visions of how community data could impact their hyper-local climate AI models. One possibility participants mentioned would be training climate AI models directly on the weather related data submitted by community members, but opinions on whether this would work were mixed. One scientist said *"Because the big thing in AI is having high quality labeled data sets. So what I would love to be able to do is actually have people report urban flooding throughout Chicago, and then we could train a model with rainfall as input and inundation reported by people as an output."* (P1). However, another scientist did not think the data would be high-quality enough saying, *"If you want to have a network that can explain something... you have to have a continuous flow of data with a certain quality... Otherwise, the network will cluster [varying quality data] differently."* (P8).

Another way to incorporate community data on weather impacts would be through model validation and testing. This was the most popular use of community data on weather impacts we heard from scientists. P2 described how it would be important to include a human side to AI model evaluation saying, "*Let's say we have a big heat wave and people mentioned that the Woodlawn area was quite a bit warmer... Not just saying that, 'Oh, the RMSC was 2.5.' Qualitatively going through and being like, 'Okay, it looks like Woodlawn was warmer than Bridgeport.' Some of these things that are more important to the human aspect and not just... our typical* *diagnostics that we use when we're going through and evaluating models."*

The final way that scientists said they could make use of community input was as a way of making sense of hyper-local climate AI model outputs. For example, P12 said there could be unexplained spikes in the sensor data for their instruments without an apparent cause:

> *"But occasionally with our different sensors on the roof, we'll get this isolated spike in carbon monoxide or something. In addition to being able to alert people nearby, [it would be helpful to ask] 'Hey, everybody look around. Are there any big trucks? Do you see any smoke plumes?'... I could see people wanting to engage with that, just like there's storm spotters and pollution spotters."*

In addition to unexplained spikes, other scientists mentioned distinguishing between categories that neighborhood sensor instruments have trouble with, such as the difference between dust and pollen which are a similar size. Lastly, community residents could help with processing complex data, for instance identifying cicada noises that an AI model might struggle with naming.

5.2 How Communities Envision Actionable Uses for Precision Weather AI

Next, we sought to understand how community members might want to use precision weather data. We found that while numerous community members hold deep expertise in local weather issues, quantitative precision weather data could be used to reinforce this knowledge and advocate for resources. When speaking with community leaders and members about how precision weather could be used in individual and community decision-making, we found interest in quantifying "bang for the buck" in green infrastructure investments, real-time alerts, and severe weather prediction.

5.2.1 Augmenting Existing Community Knowledge and Advocacy. Chatham community members told us that they had been advocating for environmental issues in their neighborhood for many years. Community members explained that Chatham sits at the intersection of two water reclamation systems that, during heavy rain, fill from the center to the periphery and can overflow into the neighborhood, flooding basements and streets. In addition, participants reported that the neighborhood sits near pollution-generating sites such as a highway that lead to poor air quality. Historically, community members felt that the neighborhood has not received the funding necessary to tackle these problems. For example, Chicago has a program where residents can call 311 if they need help with infrastructure issues such as a pothole or flooded basement. Community leader P14 explained that most residents do not call 311 due to the fact that historically the effort to report has not been met with concrete help. In the Community Cafe surveys, participants had varied responses to whether or not these services were helpful and made comments such as, "*311 operator responded with lack of concern*" and "*follow-up is terrible*." Some residents also worried that the data collected by 311 might lower the value of their homes.

While knowledge about these types of weather issues is deeply embedded in the neighborhood, community members reported that local funding bodies such as the city or grant-giving institutions often seek quantitative data to back up the claims about damaging weather impacts. P15 gave an example of a community organization that was motivated to use neighborhood level data on heat islands in their community to their advantage saying,

> *"We know that what they're trying to do is create an energy, almost economy within their community. And they have heat island issues. And so, what does that mean in terms of energy burden? They're going to want to focus on creating, instead of having energy be a burden to the community, have energy be a moneymaker for the community."*

This quote reflected what we heard from community participants in the first three Community Cafes. In fact, advocacy is a community-level application of hyper-local climate AI data, meaning it is organizations rather than individual residents that can take action on the data. This use case is also aligned with the kind of data scientists we spoke to actively used to generate for their own grant applications.

5.2.2 Weather-Related Infrastructure Investment. Community members also reported that they wanted to use precision weather and data from hyper-local climate AI models to help decide which weather adaptation strategies and investments would be most worthwhile. For example, there are a number of interventions that might soak up water and reduce flooding such as planting trees, installing bioswales, utilizing rain barrels, and updating sewage pipes to deal with flooding impacts. Residents told us they were interested in both community-wide investments (such as fixing the sewage system) as well as individual-level investments (such as adding rain barrels or sump pumps to homes). Community leader P14 summarized these community sentiments saying,

> *"Success would be having an action plan where we can look at what activities have the biggest bang for the buck [...] That we have documented that if we change where the sewer connection pipe is, or we plant 10,000 more trees, that we would have an action plan to go ahead and do that."*

Community members were also interested in data that could show which of the many flooding-related interventions would be most effective locally—particularly for limiting flooding. Community engagement specialists summarized this sentiment as being able to make informed decisions because of limited resources as in *"We don't want to guess, we want to know."*

5.2.3 Real-Time Precision Weather Alerts. Community members also emphasized the relevance of targeted real-time precision weather alerts, particularly for individual decision-making. One example residents spoke of was how their neighborhood bordered a highway and that this could be a source of unhealthy air. P14 felt that an alert function would be important since not everyone checked the weather on their own, and that the alert should be paired with information on how to act. Several Community Cafe participants also mentioned that it would be nice to have an alert for particularly good air quality, so they could garden or go on a walk. Participants wanted a real-time alert as a text message or presented on a visual map. P13, a community engagement specialist said in relation to air quality,

> *"[I'd like] an aerial landscape or map, which shows higher pollution areas... or I don't know if you can get a detail with block by block, which would be amazing... Just so people know if they're walking into something."*

Multiple Community Cafe participants also said real-time alerts would be helpful at the start of heavy rainfall that warned residents to prepare for possible basement flooding. Some noted that real-time alerts would also be helpful for flash flooding incidents and warnings for which roads to avoid when driving. More importantly, P13 mentioned that to ensure alerts have impact, the availability of the alert system must be communicated to residents which is not always easy since Chatham has many seniors without good access to information. This is a finding similar to that of [22] who mention that education and engagement are important factors for making residents aware of sensor related information (in their case for air quality sensors). P15 suggested that Chatham may have good infrastructure for such communications because they had many block clubs that operated to provide support and information at the block level.

5.2.4 Severe Weather Prediction From Precision Weather AI. In addition to real-time alerts that would tell residents when a severe weather event had already started, community members were interested in being able to predict such events in advance with hyper-local climate AI models. Community members wondered whether flooding could be predicted, and thus planned for, and possibly even prevented. Residents told us that they already have access to city-wide forecasts so precision weather could be valuable if it offered prediction. They already felt the city forecasts were often not applicable to them and wanted a neighborhood-level, and ideally block-level, prediction. Yet, P15 mentioned that prediction even for hyper-local climate AI models was hard to achieve in practice because *"The science is not going to allow for that level of mitigation effort. It is going to be longer term."*

5.3 Challenges to Community-Based Weather AI

We identified several gaps that must be bridged for precision weather to move from the lab to the community. First, there was a tension between residents' desire for high-accuracy and hyper-local prediction/real-time alerts of weather events (particularly severe ones) and scientists' tendency towards preference for a carefully curated backwards look at data since given tricky questions of accuracy and conveying uncertainty. Second, despite the fact that scientists were excited by the prospect that community members could use the data they carefully collected, there was a lack of sociotechnical interfaces to translate the data between the two groups. On the social side, there were no existing ways to communicate what data is being collected by the sensors, how it is being collected, and why it is being collected. On the technical side, there was no way to convert the raw weather data and hyper-local climate AI model outputs to a more user-friendly format. Third, the need for trust between scientists and communities—and the significant time it takes to build this trust—would be critical for precision weather applications to be successful.

5.3.1 Tension Between Residents' Desire for Real-Time Data and Scientists' Concerns About Data Quality and Uncertainty. We previously described how residents wanted a way to precisely predict severe weather events in their neighborhoods that would personally impact them. This need was in tension with scientists' desire to produce highly accurate data with error bars that measure uncertainty. For example, on a particularly foggy day scientist P1 noted in their research lack channel, *"Wonder if the fog is playing havoc with our [particulate matter] measurements today"* and showed a graph with higher than normal measurements. After some discussion, the group of scientists concluded that there was not a spike in pollution but in fact the increase was due to dense fog. Had a real-time air quality alert been deployed to the public, it would have needed to subsequently be retracted, likely damaging public trust in the data.

Prediction is even more uncertain than real-time alerts, given that nobody can know for sure what the weather will be in the future. Scientists explained that conveying this uncertainty—which is particularly high for hyper-local climate AI models—is a challenge and several we spoke with were particularly hesitant to endorse prediction as even a possibility for precision weather. P3, an atmospheric instrumentation specialist, summarized this perspective saying:

> *"The flooding information is going to be something that's years down the line. [Residents] are not going to see some real time, "Hey, it's about to flood for you." They won't ever get that. It's going to take us forever to develop something like that."*

Several scientists thought precision prediction *might* be possible, and that real-time precision weather alerts were well within the realm of possibility. Others said they would be more comfortable providing explanations and public-facing write-ups of recently past events. Community members were less interested in backwards-looking reports because this does not aid decision-making in the face of an extreme weather event—in other words, these reports were less actionable.

5.3.2 Lack of Sociotechnical Interfaces Between Scientists/Raw Sensor Data and Community Members. The scientists we interviewed were overwhelmingly excited about community members who were not professional researchers using the data they produced. P2, a software developer on the science team, said that he hoped:

> *"The people would be looking at the data all the time, especially at the community level... So we post events looking at after a storm has gone through or after there's been a big heat wave during the summer that people look to [our data] for the information there... And really just seeing the data used by the... community partners and the Chicago area, seeing it in the hands of community members."*

P4, another atmospheric science software developer, echoed this sentiment saying, *"I would like to see large scale community involvement in actually using the data we're producing."* Despite this excitement for using the data, however, no stakeholders fully grappled with the social and technical reasons community members were not equipped to seize the opportunity to work with the raw data.

Our findings revealed that there was a lack of "sociotechnical interfaces," i.e., that both social and technical interventions would be needed to realize scientists' goals of having the community *"looking at the data all the time."* On the technical side, the data was stored in several databases and required skills such as using an API, Python, and reading CSV files. Even with this skillset, conducting data science analysis is time-consuming. Community volunteers were already overworked and did not have time to dive deep on the raw data. Improving the technical interfaces, however, had to be paired with improved social interfaces. Scientists were already steeped in the *context* surrounding the raw data. This made it easy to forget the context was learned and must be shared with community members for them to engage with the data in the same way.

5.3.3 Differing Understandings of Surveillance, Community Benefit, and Trust. Both scientists and community members were aware of the need to build trust but each group emphasized slightly different viewpoints when describing how to build trust.

Scientists were primarily worried that the sensors they needed to place in neighborhoods would be interpreted as surveillance devices, particularly in areas that had been over-policed. P3, an atmospheric instrumentation specialist, voiced this concern which we heard multiple times, saying,

> *"[The community is] going to see something that has a camera on it, potentially two cameras and be like, 'What is this surveillance device doing?' So that's where I'm concerned on the community reception is if we have a camera going at all times and we say, 'Hey, it's for science,' they're going to just think we're studying them when it's not studying them. It's looking at the vegetation, the roads, the sky."*

Multiple scientists said they felt it was important to engage with community members to explain that the sensors were not spying on them. For example, atmospheric scientist P1 said scientists needed to,

> *"Help communities accept these tools, these important tools, into their neighborhoods... the answer is... critical data literacy. And then I do think it's really important for [us] to have a robust public outreach component. Lots of listening, lots of understanding the concerns of the communities, and doing things to address them."*

To be clear, community members cared deeply about privacy, raising broader concerns than scientists—for example, fears that public flood data could lower housing values. However, their primary concern was that science deliver tangible community benefits. In other words, having privacy-preserving technology was necessary but not sufficient. In addition to being over-policed, this community had been over-studied but had not seen direct benefit from most weather related research done on them. Managing recurring basement flooding and its mental and physical impacts had also taken a significant mental toll on the community, as described by numerous Community Cafe participants. P15, a community engagement strategist summarized saying, ' *'If you're going to pick [at these communities] and you're not going provide any compensation or any solution, then it's really injurious at this point."* Community leader P14 summarized the ideal way of working with scientists while seeing a "tangible" result saying,

> *"Equity looks like when the decisions are driven by the community for the community. We're telling you what's good for us and then we're working collaboratively to address the issue. I find that when we talk from a scientific lens, not based on 'please help us,' but we have the science that can inform, that if you change where that sewer pipe is and move it, about 50% of the basements will flood less. That is something that is tangible."*

P5, an atmospheric scientist who had spent time with community members reflected:

> *"Having worked with the community partners during this past year, hearing their side of the story, I see that there is this disconnect between the communities and the scientists. The scientists get excited by the science they do... But me personally, I never looked beyond that how it is going to be impacting somebody else. So now it has become kind of personal because we know those people, we have heard their stories and we have seen their discontent and distrust a little bit as well because they know we exist, we do our science, but how is it going to impact their well-being, their neighborhoods? That part is the disconnect."*

This quote shows that participating scientists developed an understanding over time that the key for building trust with the community was more than addressing privacy concerns about collected weather related data and weather impacts and about "impacting their well-being." This kind of challenge was not one scientists were accustomed to addressing for hyper-local climate AI modeling and precision weather applications.

6 Findings From Phases 3–4: Building the *Water On My Block App*

Our first three phases of research made it clear that (1) any artifacts created as part of the participatory AI process had to make the data collected actionable for both community members and scientists, (2) that the artifact had to be a mechanism for building trust between stakeholders, and that (3) the questions around data ownership, and the outcomes of collecting the data need to be transparent for hyper-local climate AI pipelines with communities and scientists.

6.1 Key Design Decisions Bringing Community and Scientist Visions For Precision Weather AI Together

We developed *Water On My Block* as part of the participatory processes to support the hyper-local climate AI pipeline between community members and scientists. This web app works on both desktop and mobile (see the screenshot in Figure 7). *Water On My Block* lets users report a flood incident, view flood incidents on a map and in a community feed, and see resources for flooding specific to Chatham. When reporting a flood incident, users are asked questions about the flood such as location (basement or street), water depth, and how long the standing water has been there. This data is important for understanding weather impacts and how that relates to neighborhood sensor data collected by the scientists for the hyper-local climate AI models. Our partner, GCI, has final say on who the data from the web app is shared with, but as part of the design, the community agreed to share relevant data with the scientists to improve precision weather and AI-based flooding models of the neighborhood.

6.2 *Water On My Block* Prototype Evaluation

Several core themes emerged from the two evaluation stages of the app (pilot testing with the scientists and community engagement specialists, and Community Cafe 3). Generally, community participants and scientists felt the tool was useful. All but 1 participant in Community Cafe 3 agreed or strongly agreed that the map interface was easy to use and 13 participants agreed or strongly agreed that the community feed was valuable. One participant said *"it is valuable information regarding traffic/travel plans and maintenance for my property. I would like to interact with the reports if I want more details."* and *"Now the people who live on the block, they are aware of what's going on in the neighborhood. "* 13/14 residents in Community Cafe 3 also said they would use the app to generate requests to the city for flooding or emails to their local representative and residents liked the resources page (e.g., the insurance information was helpful). Scientists were excited about the possibility of using the tool in all the neighborhoods where they are deploying precision weather measurement instruments to collect hyper-local reports on flooding impacts and in particular wanted to know more about whether the app could be easily adapted for this purpose.

6.2.1 Balancing Usability and Data Integrity For AI Pipelines. The evaluations surfaced resident concerns around privacy and security and the tool design. For instance, we had created a "Custom Radius" dialog that allowed users to either drop a precise pinpoint for a flood report or submit a location within a user-defined radius, adjustable in miles. However, this customizable approach raised concerns during the intermediate demos. GCI questioned whether residents would fully understand how to size their radius, or whether the annotations would lose meaning if residents submitted areas that were too vague. ANL scientists, meanwhile, noted that accepting variable radius sizes would create inconsistencies in data specificity, complicating backend data normalization and geospatial analysis. Both the community members and scientists preferred backend access to the true latitude and longitude for consistency. In response, we removed the customizable radius tool before Community Cafe 3, limiting annotation input to fixed pinpoints for the prototype shown at that event.

6.2.2 Privacy, Security, and Location Obfuscation For Communication and Advocacy. In Community Cafe 3 on the surveys, 12 of the participants reported comfort sharing with neighbors but only nine also being comfortable sharing the data with the nonprofit, and fewer wanted to share the data with scientists (6) and only three being comfortable with the information to be public. Yet in verbal statements, the feedback was more nuanced. On the one hand, several participants emphasized that when a part of Chatham flooded, they wanted to notify others not to park there and avoid walking through it with children. Residents repeatedly framed this as sharing information about what was happening *"on my block."* Some residents, on the other hand, expressed concern that insurance companies might access the data in *Water On My Block* to devalue their properties or deny future claims. At the same time, residents did not mind providing the national lab, GCI, and the Federal Emergency Management Agency (FEMA) with access to private flood reports including precise locations if this information helped these organizations understand flooding trends in Chatham. Based on these concerns, we changed the ability for community members to choose whether flood reports they create on the app are shown on the public map and feed or only shown to GCI to contribute to data gathering without disclosing their report to the wider community. We also made it optional to include images with the flood reports. In this way, GCI and the scientists are also able to gather a wider set of data without compromising any individual's privacy. GCI can also use the app's aggregated data to share with scientists to further protect individuals' privacy.

6.2.3 Refining Language and Flood Report Form Design. GCI wanted to include questions in the flood reporting form to collect relevant information on weather impact whereas scientists wanted the form to clearly delineated reports so they could associate it with certain areas on the map. At Community Cafe 3, residents found some questions confusing (e.g., what is the difference between a "gutter box" and storm drain) and asked if photos could replace completing lengthy descriptions. Yet, images alone would not provide the structured, analyzable inputs ANL researchers needed for their data science initiatives. Residents as a group also valued being able to connect the flood report to 311 to optimize attention and resources for a given flooding incident at the city level. We revised the form to be simpler so that it could be used in the planned launch in Chatham. Throughout these phases, GCI asked for us to make it easier to download and share with scientists and others to facilitate advocacy efforts and the hyper-local climate AI pipeline. Scientists similarly wanted to ensure they could feed the resulting data into their hyper-local climate AI models but in this project, we did not evaluate this from the scientists' perspective.

7 Discussion

7.1 Participatory AI as Sociotechnical Interface

The initial goal of this project was to design and develop a participatory AI system. As noted by Delgado et al. [24], while many papers claim to follow a participatory process when building AI, most merely allow stakeholders to consult rather than provide stakeholders with true ownership. A test of true ownership includes the ability to stop the AI project from being built at all. We realized that once we engaged with our stakeholders, particularly our community partner, and wanted to provide them with full ownership over the project, then we needed to let go of any particular technical outcome we originally wanted. Once we began discussions with the community partner and residents, we realized their focus was on developing what has been called a "climate service" [57]. To the community, whether this climate service involved AI or not was beside the point—what mattered is that it directly addressed community weather concerns. For the scientists building the hyper-local climate AI system, however, it was exciting to envision including community data in their models (or in the model testing). From our perspective and the perspective of the scientists who need precise data (as others have noted about climate data for science [1]), we created a system that adds community-sourced data to the hyper-local climate AI pipeline and engaged community members in the scientific process using a participatory process. Yet from the perspective of the community, we created a climate service.

Given that the app we produced (*Water On My Block*) functioned both as a means for gathering ground truth data on flooding in the neighborhood to feed into hyper-local climate AI models for scientists and as a climate service for the community, addressing the needs of each group but without requiring consensus on the ultimate goal of the app, we argue that the app functions as a boundary object. Boundary objects are artifacts that have interpretive flexibility, meaning the same object can be used/understood by different groups in distinct ways, and they also "*allow different groups to work together without consensus*" [71]. Throughout our discussions, interviews, and Community Cafes that nominally centered around the design of this app, we also provided ample opportunities for scientists and community members to learn about each other and find ways of collaborating and communicating effectively–a central goal of participatory AI. We learned that building a fully functional hyper-local climate AI pipeline is inherently time-consuming, requiring relationship building, neighborhood-level measurement infrastructure, and attention to community benefit. Even after three years, the precision weather system was still being deployed across neighborhoods in phases. Notably, even in a completed system, residents do not have direct control over the hyper-local AI models. Further work is needed to determine whether such control is feasible or desirable for all parties.

Our case study demonstrates that the participatory AI design process can be about developing a social interface as much as a technical one: the goal of crafting a technical artifact can allow for the mutual shaping of stakeholders during the process that has implications outside of the final object. It also means specifying exactly what true participation in the AI pipeline means for each stakeholder group which requires additional discussions about the pipeline, as Delgado et al. [24] outline that means revisiting what participation means, who should participate, and potential points of inclusion, consultation, collaboration, and ownership throughout the process of building this pipeline. This undertaking also requires educating all stakeholders on the possibilities so they know "what's on the table" or how they can be involved in hyper-local climate AI systems, necessitating time, attention, and further resource investment.

7.2 Engaging Stakeholders with A Community Cafe Model

Our findings suggest that the Community Cafe model is a good model for having stakeholders interact in a way that minimizes harm to underserved communities and that it can be used in participatory approaches to support hyper-local climate AI projects [19, 40, 46, 51]. While these events require significant planning to provide incentives for community members to attend and engage, they can be scheduled regularly to ensure communication between scientists and community members. In the interim, conducting intermediate demos with other relevant stakeholders as we did with Argonne National Laboratory proved useful. Moreover, having a community partner was the key to success, for instance, GCI helped to mitigate when feedback from the community and scientists diverged. As others have noted [22], this does require investing resources for stakeholders to meet. As Delgado et al. [24] suggest this model can enable community members and researchers to consult with each other, for their voices to be included on design decisions, and for collaborations around designs. The role of being an owner in the AI pipeline however is not easy to achieve with this model alone since the full pipeline requires scientists to also actively engage in the Community Cafes which requires more work on the part of planning and executing these cafes. Additionally, ownership in this project was better achieved not at the individual level, but by the community partner organization itself which could represent the community as a whole. Thus the Community Cafe model is only one tool but not a panacea for participatory approaches to community involvement in hyper-local climate AI projects.

The Community Cafe discussions also revealed that community residents are not a monolith; they bring diverse histories, risks, and comfort levels to the table. This revealed how participatory AI functions not merely as a means of gathering feedback but also as a governance model: one that redistributes decision-making authority to the community. Creating *Water On My Block* essentially exposed "data as relations" as raised by Soden et al [70] and how precision weather data and AI models could enable local communities to advocate for themselves. In fact, residents and GCI considered making flood reports with *Water On My Block* as a form of civic witnessing—a collective record that could validate their experiences and demand future accountability. We therefore suggest that a Community Cafe model of working with communities for participatory AI can be a thoughtful way to engage communities in data as relations work. It does not, however, resolve all issues in terms of power dynamics between scientists and community members. By its very nature, there is some technical knowledge and know-how that cannot be easily shared about the hyper-local climate AI pipeline such as how the edge computing and AI models analyze data from neighborhood measurement tools, or use the data gathered from the community. Creating educational programs, such as a data ambassador program, that enable community members to more directly engage with, understand, and control the data from neighborhood measurement instruments and create reports and visualizations from the resulting hyper-local climate AI models may help to even the playing field in terms of knowledge building. This kind of program—requiring time, resources, and investment of its own—would compliment a Community Cafe model to improve participation from community members in climate AI pipelines that rely on accurate data about and from communities. Data ambassador programs can also help scientists better communicate, get to know, and help train future scientists in the neighborhoods in which their hyper-local climate AI models are meant to serve and in which their instruments are embedded.

7.3 Community Data Partners For Participatory AI Pipelines

We have shown in this project that over the course of multiple years, with a highly targeted project, where the AI is a relatively small-scale machine learning system, we could align stakeholders in a participatory design process. But this begs the question as to whether this kind of method for developing AI can scale. Some researchers have noted that annotator diversity at the individual level is crucial for inclusive AI systems [44]. To this end, we propose the concept of "community data partners." at the community level, i.e., where members of a community annotate or provide data as opposed to individuals. This may rely on a forming a relationship with a community partner as it did in our project with GCI to avoid performative or token participation or participation that is not really inclusive [19, 40, 51]. AI system builders can partner with communities to have a way of collecting high quality, community-scale data over longer time periods. To do this, a long-term engagement built on trust is critical. The system must provide direct benefit for the community data partner. Lastly, the community must have a degree of data ownership or ability to limit who the data is shared with, requiring careful consideration from the onset of **data governance**. This includes discussions around data ownership, data access, who can contribute data, and what policies are in place to preserve privacy and security, at the very least. If these requirements are met, there is the possibility for large institutions or companies building AI at scale to partner with communities.

This is a design approach unlike those in existing AI systems which often extract data from individuals—such as through crowdsourcing platforms like Amazon Mechanical Turk—without creating reciprocal value for communities. In our work, we created an app using a participatory approach where community-collected data could potentially be used for AI model training but also made actionable for the community itself. Future research could explore sustainable strategies for building long-term, mutually beneficial data partnerships with communities. Of course, this also requires careful consideration of those who are intending to partner with communities and how that aligns with community interests (e.g., some note that commercial interests to turn a profit, avoid backlash, and not be seen as exploitative can hamper collaborations [39]).

Key challenges include structuring incentives for participation and designing AI systems that provide meaningful, tangible benefits in return. Working with community data partners also means managing expectations around **ownership transfer** and **sustainability**. From the outset, we had to engage our community partner and the national laboratory in planning for ownership transfer, revisiting these discussions throughout the project. Despite this engagement, the transfer still posed challenges: most technical expertise resided within our research team, requiring us to design the app to need minimal maintenance and avoid high monthly costs. We also committed to limited post-project support. These factors highlight how successful ownership transfer demands careful planning and imposes financial and technical burdens on community data partners seeking to remain a part of a hyper-local climate AI pipeline. In essence, achieving genuine public participation in AI requires substantial time investment [19, 76] and multi-year collaboration with community data partners. It also depends on partners' willingness and capacity to maintain and manage the parts of the AI pipeline that belong to them. This ties directly to sustainability—what happens after the researchers depart—a longstanding concern in participatory design [45], and in participatory AI where avoiding "parachute science" is essential [68].

In our case study, sustaining the project and app beyond the funded partnership between the community, our university-based research team and the national laboratory was a major challenge—a concern that similarly applies to community partnerships with government or even commercial entities. Although ANL funding factored in the time and human resources required for each community partner to dedicate to the climate AI project, university funding did not cover community partners' labor. This reflects a broader pattern where funders overlook the human labor necessary to power community-centered work. Such gaps are especially consequential when working with marginalized user groups whose time and labor may often be undervalued and who face heightened risks of exploitation. These limitations create a sustainability paradox: participatory design may position communities for genuine ownership over parts of an AI pipeline but prevailing funding models rarely support the multi-year engagement needed [31] for truly participatory AI systems. Achieving participatory design that matters [9] requires institutional changes to funding structures to support long term collaboration and recognize that projects of this nature unfold over years—not months, or weeks—both to fully set up the AI pipeline and to engage deeply and fully with communities.

Using participatory design with marginalized communities also requires balancing democratic participation in the AI pipeline with respect for community members time and labor. Throughout our multi-year project, we were mindful of the burden placed on the nonprofit organization and the community to engage in the participatory process. Working closely with our community partner was essential as they ensured that residents' time was used appropriately. This also meant that some early decisions—such as building an app—drew more heavily on input from the nonprofit than individual residents initially. We did not make these decisions lightly. Although we did not highlight race in our findings, the climate scientists were primarily white and the community members were predominately Black residents of a historically underserved neighborhood with a long history of research engagement that did not always yield long-lasting impact. We sought to avoid repeating these harms. Participation patterns also showed that most repeat Community Cafe attendees were retired indicating challenges in engaging younger or full-time employed residents. Ultimately, determining what meaningful participation looks like in marginalized communities requires attention to historical relations, existing power dynamics and the burdens of participation—especially when the outcomes shape AI pipelines that materially affect communities. As others have noted [77], this raises important questions about the scalability of participatory design in such contexts.

As AI applications increasingly engage entire communities rather than individual users, ethical and community-centered approaches to data collection become essential. This shift requires drawing lessons from participatory design which has already demonstrated how difficult it is to sustain continuous user engagement when projects scale up [77] and expanding participatory AI methods to operate effectively at the community level. In HCI today, few projects that use participatory design (even when not restricted to involving AI) engage users at the community level [54]. Thus, HCI researchers have an important role to play to develop and document case studies of participatory approaches to support climate AI and other AI applications that depend on community data partners. Creating *Water On My Block* as an artifact also resulted in media attention being brought to flooding issues in Chatham, a positive outcome from a research perspective. Future work can focus on developing participatory AI techniques tailored for community-level engagement and address power asymmetries—cultural, racial, gender, education, income, and knowledge—that arise when diverse groups are expected to participate in shared AI infrastructures. Future work in HCI can also focus on developing participatory AI artifacts as a means to call attention to deep infrastructural issues.

7.4 Towards Participatory AI In Real-World Settings More Generally

In our study, participants were primarily focused on solving familiar, persistent problems—such as staying healthy with poor air quality or coping with urban flooding. While AI brought novel technical capabilities to these issues, participants cared less about the AI itself and more about whether it tangibly helped improve their lives. Flooding is not a new problem; what matters is whether a new approach offers real progress. However, AI differs from prior tools: it often has opaque functionality and unclear data flows. This creates unique challenges for everyday adoption. When people are offered help with serious, ongoing challenges—such as chronic infrastructure issues—they are generally open to trying new solutions. But when the technology extracts data without obvious community benefit, trust becomes fragile. People are not only evaluating whether the tool works; they are assessing how it fits into their understanding of the social world, and how it might shift their own position within this world.

From this, two lessons stand out: first, AI systems must provide clear, meaningful value that is legible and aligned with users' real needs. Second, AI system designers must recognize that they are intervening in social structures—potentially altering power dynamics based on decisions such as whose culture the AI mimics, what labor the AI can replicate, and where the AI system concentrates the benefit of collected data. Interface and interaction design choices can help guide users in understanding the purpose of an AI system, building appropriate expectations, and shaping how they relate to it. Engaging with people in real-world environments also requires deep, sustained relationship-building. Trust does not come from design principles alone—it is built through time, presence, and accountability. Future work in participatory AI for HCI researchers, companies, government, and science organizations needs to be mindful of these commitments required to similarly align diverse stakeholder needs and move toward a collective vision; all essentials for building inclusive, human-centered AI systems.

7.5 Limitations

Due to project timeline constraints, the final flood reporting data generated by the app was not evaluated from the scientists' perspective although scientists commented and provided feedback on the prototype throughout the project and prior to deployment. Future work could include analysis of the post-app deployment stage and study the deployment of the Chatham measurement instrument to see how participatory AI relationships evolve after several years.

8 Conclusion

In this project, we partnered with climate scientists and a Chicago community organization to develop infrastructure to support hyper-local climate AI models using a participatory approach for sustained community engagement. Through participant observation, interviews, and co-design workshops ("Community Cafes") we learned about the needs of each stakeholder. We ultimately co-designed and developed an app called *Water On My Block* to allow neighborhood residents to report flooding incidents that are both displayed on a website and can be used as input for hyper-local climate AI models and to support community advocacy efforts for investments in green infrastructure in their neighborhoods. We describe stakeholder needs for precision weather, challenges to bridging the gap between scientists and community members, and lessons learned in the development of the app. By centering inclusion and participatory design, our case study illustrates how much work is involved to achieve truly participatory AI systems with community data partners. Given that AI continues to advance at an unprecedented pace, researchers, designers, and funders must work together to create community-centered approaches and enable participation from communities in AI systems that are just, equitable, and attuned to the diverse ways humans live, work, and interact socially.

Acknowledgments

We thank the anonymous reviewers for their valuable feedback on this paper. We also thank the climate scientists from Argonne National Laboratory, Greater Chatham Initiative, and Chatham residents who participated in this project. We also thank Mike Ingber and Noah Lindner for consulting on the *Water On My Block* design and implementation. This project was funded by a University of Chicago BIG grant and the Mansueto Institute for Urban Innovation.

References

[1] Paul Aoki, Allison Woodruff, Baladitya Yellapragada, and Wesley Willett. 2017. Environmental Protection and Agency: Motivations, Capacity, and Goals in Participatory Sensing. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 3138–3150. https://doi.org/10.1145/3025453.3025667

[2] Maria Aristeidou, Eileen Scanlon, and Mike Sharples. 2015. Weather-it: evolution of an online community for citizen inquiry. In *Proceedings of the 15th International Conference on Knowledge Technologies and Data-driven Business (i-KNOW '15)*. Association for Computing Machinery, New York, NY, USA, 1–8. https://doi.org/10.1145/2809563.2809567

[3] Mara Balestrini, Yvonne Rogers, Carolyn Hassan, Javi Creus, Martha King, and Paul Marshall. 2017. A City in Common: A Framework to Orchestrate Large-scale Citizen Engagement around Urban Issues. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 2282–2294. https://doi.org/10.1145/3025453.3025915

[4] Liam Bannon, Jeffrey Bardzell, and Susanne Bødker. 2018. Reimagining participatory design. *Interactions* 26, 1 (Dec. 2018), 26–32. https://doi.org/10.1145/3292015

[5] Oliver Bates, Vanessa Thomas, Christian Remy, Lisa P. Nathan, Samuel Mann, and Adrian Friday. 2018. The Future of HCI and Sustainability: Championing Environmental and Social Justice.. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI EA '18)*. Association for Computing Machinery, New York, NY, USA, 1–4. https://doi.org/10.1145/3170427.3185365

[6] Abeba Birhane, William Isaac, Vinodkumar Prabhakaran, Mark Diaz, Madeleine Clare Elish, Iason Gabriel, and Shakir Mohamed. 2022. Power to the People? Opportunities and Challenges for Participatory AI. In *Proceedings of the 2nd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization* (Arlington, VA, USA) *(EAAMO '22)*. Association for Computing Machinery, New York, NY, USA, Article 6, 8 pages. https://doi.org/10.1145/3551624.3555290

[7] Abeba Birhane, Atoosa Kasirzadeh, David Leslie, and Sandra Wachter. 2023. Science in the age of large language models. *Nat Rev Phys* 5, 5 (April 2023), 277–280. https://doi.org/0.1038/s42254-023-00581-4

[8] Susanne Bødker, Christian Dindler, Ole S Iversen, and Rachel C Smith. 2022. What is participatory design? In *Participatory design*. Springer, 5–13.

[9] Susanne Bødker and Morten Kyng. 2018. Participatory Design that Matters—Facing the Big Issues. *ACM Trans. Comput.-Hum. Interact.* 25, 1, Article 4 (Feb. 2018), 31 pages. https://doi.org/10.1145/3152421

[10] Elizabeth Bondi, Lily Xu, Diana Acosta-Navas, and Jackson A. Killian. 2021. Envisioning Communities: A Participatory Approach Towards AI for Social Good. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society* (Virtual Event, USA) *(AIES '21)*. Association for Computing Machinery, New York, NY, USA, 425–436. https://doi.org/10.1145/3461702.3462612

[11] Alejandra Borunda. 2025. Trump officials signal potential changes at NOAA, the weather and climate agency. *NPR* (Feb. 2025). https://www.npr.org/2025/02/15/nx-s1-5297183/noaa-national-weather-service-trump

[12] Anne Bowser, Katie Shilton, Jenny Preece, and Elizabeth Warrick. 2017. Accounting for Privacy in Citizen Science: Ethical Research in a Context of Openness. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*. Association for Computing Machinery, New York, NY, USA, 2124–2136. https://doi.org/10.1145/2998181.2998305

[13] Virginia Braun and Victoria Clarke. 2012. Thematic analysis. In *APA handbook of research methods in psychology Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological Edition*. American Psychological Association, 57–71.

[14] Christina Bremer, Bran Knowles, and Adrian Friday. 2022. Have We Taken On Too Much?: A Critical Review of the Sustainable HCI Landscape. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3491102.3517609

[15] Scott Bremer, Arjan Wardekker, Suraje Dessai, Stefan Sobolowski, Rasmus Slaattelid, and Jeroen van der Sluijs. 2019. Toward a multi-faceted conception of co-production of climate services. *Climate Services* 13 (2019), 42–50. https://doi.org/10.1016/j.cliser.2019.01.003

[16] Jerald A. Brotzge, J. Wang, C. D. Thorncroft, E. Joseph, N. Bain, N. Bassill, N. Farruggio, J. M. Freedman, K. Hemker, D. Johnston, E. Kane, S. McKim, S. D. Miller, J. R. Minder, P. Naple, S. Perez, James J. Schwab, M. J. Schwab, and J. Sicker. 2020. A Technical Overview of the New York State Mesonet Standard Network. *Journal of Atmospheric and Oceanic Technology* 37, 10 (2020), 1827 – 1845. https://doi.org/10.1175/JTECH-D-19-0220.1

[17] World Cafe. 2015. The World Cafe Method. https://theworldcafe.com/key-concepts-resources/world-cafe-method/

[18] Charlie Catlett, Pete Beckman, Nicola Ferrier, Michael E. Papka, Rajesh Sankaran, Jeff Solin, Valerie Taylor, Douglas Pancoast, and Daniel Reed. 2022. Hands-On Computer Science: The Array of Things Experimental Urban Instrument. *Computing in Science & Engineering* 24, 1 (2022), 57–63. https://doi.org/10.1109/MCSE.2021.3139405

[19] Eric Corbett, Remi Denton, and Sheena Erete. 2023. Power and Public Participation in AI. In *Proceedings of the 3rd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization* (Boston, MA, USA) *(EAAMO '23)*. Association for Computing Machinery, New York, NY, USA, Article 8, 13 pages. https://doi.org/10.1145/3617694.3623228

[20] Eric Corbett and Christopher Le Dantec. 2021. Designing Civic Technology with Trust. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, 1–17. https://doi.org/10.1145/3411764.3445341

[21] Sasha Costanza-Chock. 2020. *Design Justice: Community-Led Practices to Build the Worlds We Need*. The MIT Press, Cambridge, MA.

[22] Madeleine I. G. Daepp, Alex Cabral, Tiffany M Werner, Raed Mansour, Charlie Catlett, Asta Roseway, Chuck Needham, Nneka Udeagbala, and Scott Counts. 2023. The "Three-Legged Stool": Designing for Equitable City, Community, and Research Partnerships in Urban Environmental Sensing. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–19. https://doi.org/10.1145/3544548.3581289

[23] Fernando Delgado, Stephen Yang, Michael Madaio, and Qian Yang. 2021. Stakeholder Participation in AI: Beyond "Add Diverse Stakeholders and Stir". arXiv:2111.01122 (Nov. 2021). https://doi.org/10.48550/arXiv.2111.01122 arXiv:2111.01122 [cs].

[24] Fernando Delgado, Stephen Yang, Michael Madaio, and Qian Yang. 2023. The Participatory Turn in AI Design: Theoretical Foundations and the Current State of Practice. In *Proceedings of the 3rd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization (EAAMO '23)*. Association for Computing Machinery, New York, NY, USA, 1–23. https://doi.org/10.1145/3617694.3623261

[25] Emily Denton, Alex Hanna, Razvan Amironesei, Andrew Smart, Hilary Nicole, and Morgan Klaus Scheuerman. 2020. Bringing the People Back In: Contesting Benchmark Machine Learning Datasets. *CoRR* abs/2007.07399 (2020). arXiv:2007.07399 https://arxiv.org/abs/2007.07399

[26] Betsy DiSalvo. 2016. Participatory Design through a Learning Science Lens. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 4459–4463. https://doi.org/10.1145/2858036.2858405

[27] Carl DiSalvo, Ann Light, Tad Hirsch, Christopher A. Le Dantec, Elizabeth Goodman, and Katie Hill. 2010. HCI, communities and politics. In *CHI '10 Extended Abstracts on Human Factors in Computing Systems* (Atlanta, Georgia, USA) *(CHI EA '10)*. Association for Computing Machinery, New York, NY, USA, 3151–3154. https://doi.org/10.1145/1753846.1753940

[28] Carl DiSalvo, Phoebe Sengers, and Hrönn Brynjarsdóttir. 2010. Mapping the landscape of sustainable HCI. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1975–1984.

[29] Joseph Donia and James A. Shaw. 2021. Co-design and ethical artificial intelligence for health: An agenda for critical research and practice. *Big Data & Society* 8, 2 (2021), 20539517211065248. https://doi.org/10.1177/20539517211065248 arXiv:https://doi.org/10.1177/20539517211065248

[30] Pelle Ehn. 1988. Work-oriented design of computer artifacts. (1988). https://urn.kb.se/resolve?urn=urn:nbn:se:umu:diva-62913

[31] Salma Elsayed-Ali, Elizabeth Bonsignore, and Joel Chan. 2023. Exploring Challenges to Inclusion in Participatory Design From the Perspectives of Global North Practitioners. *Proc. ACM Hum.-Comput. Interact.* 7, CSCW1, Article 130 (April 2023), 25 pages. https://doi.org/10.1145/3579606

[32] Sheena L. Erete. 2014. Community, Group and Individual: A Framework for Designing Community Technologies. *The Journal of Community Informatics* 10, 11 (2014). https://doi.org/10.15353/joci.v10i1.2671

[33] Michael Feffer, Michael Skirpan, Zachary Lipton, and Hoda Heidari. 2023. From Preference Elicitation to Participatory ML: A Critical Survey & Guidelines for Future Research. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society* (Montréal, QC, Canada) *(AIES '23)*. Association for Computing Machinery, New York, NY, USA, 38–48. https://doi.org/10.1145/3600211.3604661

[34] Chicago Metropolitan Agency for Planning. 2024. *Chatham Community Data Snapshot*. Technical Report.

[35] Jennifer Gabrys. 2022. *Citizens of Worlds: Open-Air Toolkits for Environmental Struggle*. Univ Of Minnesota Press, Minneapolis.

[36] Ya'akov (Kobi) Gal, Avi Segal, Ece Kamar, Eric Horvitz, Chris Lintott, and Mike Walmsley. 2022. A new Workflow for Human-AI Collaboration in Citizen Science. In *Proceedings of the 2022 ACM Conference on Information Technology for Social Good (GoodIT '22)*. Association for Computing Machinery, New York, NY, USA, 89–95. https://doi.org/10.1145/3524458.3547243

[37] Daniel Gooch, Matthew Barker, Lorraine Hudson, Ryan Kelly, Gerd Kortuem, Janet Van Der Linden, Marian Petre, Rebecca Brown, Anna Klis-Davies, Hannah Forbes, Jessica Mackinnon, Robbie Macpherson, and Clare Walton. 2018. Amplifying Quiet Voices: Challenges and Opportunities for Participatory Design at an Urban Scale. *ACM Trans. Comput.-Hum. Interact.* 25, 1, Article 2 (Jan. 2018), 34 pages. https://doi.org/10.1145/3139398

[38] Mary L. Gray and Siddharth Suri. 2019. *Ghost Work: How to Stop Silicon Valley from Building a New Global Underclass*. Houghton Mifflin Harcourt, Boston.

[39] Lara Groves, Aidan Peppin, Andrew Strait, and Jenny Brennan. 2023. Going public: the role of public participation approaches in commercial AI labs. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 1162–1173. https://doi.org/10.1145/3593013.3594071

[40] Christina Harrington, Sheena Erete, and Anne Marie Piper. 2019. Deconstructing Community-Based Collaborative Design: Towards More Equitable Participatory Design Engagements. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 216 (Nov. 2019), 25 pages. https://doi.org/10.1145/3359318

[41] C. Howarth, M. Lane, S. Morse-Jones, K. Brooks, and D. Viner. 2022. The 'co' in co-production of climate action: Challenging boundaries within and between science, policy and practice. *Global Environmental Change* 72 (2022), 102445. https://doi.org/10.1016/j.gloenvcha.2021.102445

[42] Candice Howarth and Irene Monasterolo. 2017. Opportunities for knowledge co-production across the energy-food-water nexus: Making interdisciplinary approaches work for better climate decision making. *Environmental Science & Policy* 75 (2017), 103–110. https://doi.org/10.1016/j.envsci.2017.05.019

[43] Sheila Jasanoff. 2004. The idiom of co-production. In *States of knowledge*. Routledge, 1–12.

[44] Shivani Kapania, Alex S Taylor, and Ding Wang. 2023. A hunt for the Snark: Annotator Diversity in Data Practices. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 133, 15 pages. https://doi.org/10.1145/3544548.3580645

[45] Finn Kensing and Jeanette Blomberg. 1998. Participatory design: Issues and concerns. *Computer supported cooperative work (CSCW)* 7, 3 (1998), 167–185.

[46] Christopher A. Le Dantec and Sarah Fox. 2015. Strangers at the Gate: Gaining Access, Building Rapport, and Co-Constructing Community-Based Research. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing* (Vancouver, BC, Canada) *(CSCW '15)*. Association for Computing Machinery, New York, NY, USA, 1348–1358. https://doi.org/10.1145/2675133.2675147

[47] Peiyuan Li and Ashish Sharma. 2024. Hyper-local temperature prediction using detailed urban climate informatics. *Journal of Advances in Modeling Earth Systems* 16, 3 (2024), e2023MS003943.

[48] Jonne Maas and Aarón Moreno Inglés. 2024. Beyond Participatory AI. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* 7 (Oct. 2024), 932–942. https://doi.org/10.1609/aies.v7i1.31693

[49] Maria Isabel Magaña and Katie Shilton. 2025. Frameworks, Methods and Shared Tasks: Connecting Participatory AI to Trustworthy AI Through a Systematic Review of Global Projects. In *Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency (FAccT '25)*. Association for Computing Machinery, New York, NY, USA, 2166–2179. https://doi.org/10.1145/3715275.3732148

[50] Michael J. Muller and Allison Druin. 2012. *The human–computer interaction handbook: Fundamentals, evolving technologies, and emerging applications.* CRC Press, Boca Raton, Fla., Chapter 49, 1125–1153.

[51] Andrea G. Parker, Laura M. Vardoulakis, Jatin Alla, and Christina N. Harrington. 2025. Participatory AI Considerations for Advancing Racial Health Equity. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 803, 24 pages. https://doi.org/10.1145/3706598.3713165

[52] Nathan R. Prestopnik and Kevin Crowston. 2012. Citizen science system assemblages: understanding the technologies that support crowdsourced science. In *Proceedings of the 2012 iConference (iConference '12)*. Association for Computing Machinery, New York, NY, USA, 168–176. https://doi.org/10.1145/2132176.2132198

[53] Danial Qaurooni, Ali Ghazinejad, Inna Kouper, and Hamid Ekbia. 2016. Citizens for Science and Science for Citizens: The View from Participatory Design. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. Association for Computing Machinery, New York, NY, USA, 1822–1826. https://doi.org/10.1145/2858036.2858575

[54] Xiang Qi and Junnan Yu. 2025. Participatory Design in Human-Computer Interaction: Cases, Characteristics, and Lessons. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 804, 26 pages. https://doi.org/10.1145/3706598.3713436

[55] Organizers Of Queerinai, Anaelia Ovalle, Arjun Subramonian, Ashwin Singh, Claas Voelcker, Danica J. Sutherland, Davide Locatelli, Eva Breznik, Filip Klubicka, Hang Yuan, Hetvi J, Huan Zhang, Jaidev Shriram, Kruno Lehman, Luca Soldaini, Maarten Sap, Marc Peter Deisenroth, Maria Leonor Pacheco, Maria Ryskina, Martin Mundt, Milind Agarwal, Nyx Mclean, Pan Xu, A Pranav, Raj Korpan, Ruchira Ray, Sarah Mathew, Sarthak Arora, St John, Tanvi Anand, Vishakha Agrawal, William Agnew, Yanan Long, Zijie J. Wang, Zeerak Talat, Avijit Ghosh, Nathaniel Dennler, Michael Noseworthy, Sharvani Jha, Emi Baylor, Aditya Joshi, Natalia Y. Bilenko, Andrew Mcnamara, Raphael Gontijo-Lopes, Alex Markham, Evyn Dong, Jackie Kay, Manu Saraswat, Nikhil Vytla, and Luke Stark. 2023. Queer In AI: A Case Study in Community-Led Participatory AI. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 1882–1895. https://doi.org/10.1145/3593013.3594134

[56] Bryan Rickens and Navid Hashemi Tonekaboni. 2023. Towards High Resolution Urban Heat Analysis: Incorporating Thermal Drones to Enhance Satellite Based Urban Heatmaps. In *Companion Proceedings of the ACM Web Conference 2023* (Austin, TX, USA) *(WWW '23 Companion)*. Association for Computing Machinery, New York, NY, USA, 707–714. https://doi.org/10.1145/3543873.3587682

[57] Jacob M Rigby and Chris Preist. 2023. Towards User-Centred Climate Services: the Role of Human-Computer Interaction. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3544548.3580663

[58] Chiara Rossitto. 2021. Political Ecologies of Participation: Reflecting on the Long-term Impact of Civic Projects. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 187 (April 2021), 27 pages. https://doi.org/10.1145/3449286

[59] Chiara Rossitto, Rob Comber, Jakob Tholander, and Mattias Jacobsson. 2022. Towards Digital Environmental Stewardship: the Work of Caring for the Environment in Waste Management. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 335, 16 pages. https://doi.org/10.1145/3491102.3517679

[60] Dana Rotman, Jenny Preece, Jen Hammock, Kezee Procita, Derek Hansen, Cynthia Parr, Darcy Lewis, and David Jacobs. 2012. Dynamic changes in motivation in collaborative citizen-science projects. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work (CSCW '12)*. Association for Computing Machinery, New York, NY, USA, 217–226. https://doi.org/10.1145/2145204.2145238

[61] Manaswi Saha, Michael Saugstad, Hanuma Maddali, Aileen Zeng, Ryan Holland, Steven Bower, Aditya Dash, Sage Chen, Anthony Li, Kotaro Hara, and Jon Froehlich. 2019. Project Sidewalk: A Web-based Crowdsourcing Tool for Collecting Sidewalk Accessibility Data At Scale. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems.* https://doi.org/10.1145/3290605.3300292

[62] Johnny Saldañna. 2013. *The Coding Manual for Qualitative Researchers* (2nd ed ed.). SAGE, Los Angeles.

[63] Nithya Sambasivan, Shivani Kapania, Hannah Highfill, Diana Akrong, Praveen Paritosh, and Lora M Aroyo. 2021. "Everyone wants to do the model work, not the data work": Data Cascades in High-Stakes AI. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 39, 15 pages. https://doi.org/10.1145/3411764.3445518

[64] Daniel Schien, Paul Shabajee, James Wickenden, William Picket, Glynn Roberts, and Chris Preist. 2022. Demo: The DIMPACT Tool for Environmental Assessment of Digital Services. In *ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies (COMPASS) (COMPASS '22)*. Association for Computing Machinery, New York, NY, USA, 701–703. https://doi.org/10.1145/3530190.3542932

[65] Jacquelyn Q Schmidt. 2022. Climate Resiliency Through Data: Managing Stormwater Sewers in Detroit. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems (CHI EA '22)*. Association for Computing Machinery, New York, NY, USA, 1–5. https://doi.org/10.1145/3491101.3516804

[66] M. Six Silberman, Lisa Nathan, Bran Knowles, Roy Bendor, Adrian Clear, Maria Håkansson, Tawanna Dillahunt, and Jennifer Mankoff. 2014. Next steps for sustainable HCI. *Interactions* 21, 5 (Sept. 2014), 66–69. https://doi.org/10.1145/2651820

[67] Nate Silver. 2015. *The Signal and the Noise: Why So Many Predictions Fail–but Some Don't* (illustrated edition ed.). Penguin Books, New York, NY.

[68] Mona Sloane, Emanuel Moss, Olaitan Awomolo, and Laura Forlano. 2022. Participation Is not a Design Fix for Machine Learning. In *Proceedings of the 2nd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization* (Arlington, VA, USA) *(EAAMO '22)*. Association for Computing Machinery, New York, NY, USA, Article 1, 6 pages. https://doi.org/10.1145/3551624.3555285

[69] Jaime Snyder. 2017. Vernacular Visualization Practices in a Citizen Science Project. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*. Association for Computing Machinery, New York, NY, USA, 2097–2111. https://doi.org/10.1145/2998181.2998239

[70] Robert Soden, Taneea S Agrawaal, Austin Lord, Cassandra Chanen, Lillian Flawn, Zeina Seaifan, Michael Classens, and Steve Easterbrook. 2025. Climate Data Practices: A Research Approach for HCI and Climate Justice. *ACM Trans. Comput.-Hum. Interact.* (Feb. 2025). https://doi.org/10.1145/3719346 Just Accepted.

[71] Susan Leigh Star. 2010. This is not a boundary object: Reflections on the origin of a concept. *Science, technology, & human values* 35, 5 (2010), 601–617.

[72] Marita Sturken. 2001. Desiring the Weather: El Nino, the Media, and California Identity. *Public Culture* 13, 2 (2001), 161–189.

[73] Marita Sturken. 2014. Seeing the Temperature in Weather Media. (2014).

[74] Harini Suresh, Rajiv Movva, Amelia Lee Dogan, Rahul Bhargava, Isadora Cruxen, Angeles Martinez Cuba, Guilia Taurino, Wonyoung So, and Catherine D'Ignazio. 2022. Towards Intersectional Feminist and Participatory ML: A Case Study in Supporting Feminicide Counterdata Collection. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency (FAccT '22)*. Association for Computing Machinery, New York, NY, USA, 667–678. https://doi.org/10.1145/3531146.3533132

[75] A. Wang, S. Mora, Y. Machida, P. de Souza, S. Paul, O. Oyinlola, F. Duarte, and C. Ratti. 2023. Hyperlocal environmental data with a mobile platform in urban environments. *Scientific data* 10, 1 (2023), 524.

[76] Meg Young, Upol Ehsan, Ranjit Singh, Emnet Tafesse, Michele Gilman, Christina Harrington, and Jacob Metcalf. 2024. Participation versus scale: Tensions in the practical demands on participatory AI. *First Monday* (April 2024). https://doi.org/10.5210/fm.v29i4.13642

[77] Øivind Klungseth Zahlsen, Elena Parmiggiani, and Yngve Dahl. 2023. Challenges of Scaling Participatory Design: A Systematic Literature Review. In *Proceedings of the 34th Australian Conference on Human-Computer Interaction* (Canberra, ACT, Australia) *(OzCHI '22)*. Association for Computing Machinery, New York, NY, USA, 143–159. https://doi.org/10.1145/3572921.3572924

A Supplementary Materials

A.1 Scientist Interview Protocol

- Work Background and Argonne National Laboratory Initiative Goals
  (1) How would you describe the goal of your work to non-expert friends or family?
  (2) How would you describe the goal of your work to academics in your field?
  (3) How would you explain the main goal of the initiative at Argonne National Laboratory more broadly? Could you explain how your work is part of or relates to the Argonne National Laboratory project?
  (4) If the Argonne National Laboratory initiative were successful, what would that look like to you?
- Drawing Exercise
  (1) Could you please draw the Argonne National Laboratory initiative's data pipeline as you understand it.
  (2) Could you please annotate your drawing with what your research is contributing.
- Communities + Argonne National Laboratory Initiative Data
  (1) Did you grow up in the Chicago area?
  (2) What neighborhood of Chicago do you live in?
  (3) As a Chicago resident, do you feel you have the tools to manage the impact of climate change / climate change regulation on you personally?
  (4) Can you tell me about any examples of climate-related actions you have taken outside of work?
  (5) Are there other Chicago neighborhoods you are very familiar with?
  (6) Do you have some idea about where in Chicago the nodes (Argonne National Laboratory climate sensor stations) are going? How do you think these communities will feel about the nodes? How do you think these communities could benefit from the data?
  (7) Now assume your community was getting an ANL node. How do you think your community would feel about the node? How do you think your community could use the data? (Any differences with other communities?)
  (8) If you could pick any Argonne National Laboratory initiative's data to be put in a visualization for non-experts, what would it be and why?
  (9) Other than the academic community and Chicago neighborhood organizations, what other stakeholders could benefit from understanding Argonne National Laboratory initiative's data?
- Chicago and Climate Change
  (1) 1. Do you know how your work / Argonne National Laboratory's initiative fit in more broadly with the effort to address climate change in Chicago? Please explain. 2. To what extent do you think Chicago is prepared for climate change? 3. What do you think are the main areas of concern Chicago must address to be better prepared for climate change? 4. What are other things scientists could be doing to prepare for climate change in urban areas like Chicago?

A.2 Demographics Survey For Interviewees

Please fill out this brief demographics survey:

Demographics
(Written survey)

(1) What is your age?
  (a) Under 24
  (b) 25-34
  (c) 35-44
  (d) 45-54
  (e) 55-64
  (f) 65-74
  (g) 75+
(2) What is your gender?
  (a) Female identifying
  (b) Male identifying
  (c) Non-binary
  (d) Prefer not to answer
  (e) Prefer to self-describe:
(3) Which category best describes you?
  (a) American Indian or Alaska Native
  (b) Asian
  (c) Black or African American
  (d) Hispanic, Latino, or Spanish origin
  (e) Middle Eastern or North African
  (f) Native Hawaiian or Pacific Islander
  (g) White
  (h) Prefer not to answer
  (i) Prefer to self-describe
(4) What is your highest level of education?
  (a) Less than high school degree
  (b) High school degree
  (c) Associate's / Some college degree
  (d) Bachelor's degree
  (e) Master's degree
  (f) Doctoral degree
  (g) Prefer not to answer
(5) What is your occupation title?
(6) How many years have you worked in research?
(7) How many years/months have you worked in Argonne National Laboratory?

A.3 Community Member Interview Protocol

Hello! Thank you for taking the time to chat about urban climate change in Chicago. We really value hearing your perspective. This interview will last between 30 and 45 minutes. Here is the consent form. Please read it over and let me know if you have any questions. We will record the interview, but all transcripts will be anonymized and not shared outside the University of Chicago research team. Great, I'm now going to start the recording.

- Community Background and Climate Goals
  (1) What community do you live in and how long have you lived there?
  (2) In what ways are you involved in your community?

(3) What do you think are the current or future impacts of climate change on your community?
(4) Do you feel your community has the tools to manage the impact of climate change and climate change regulation that you mentioned?
(5) Can you tell me about any examples of climate-related actions you have taken?
(6) To what extent do you think Chicago is prepared for climate change?

- Communities and Argonne National Laboratory Initiative's Data

(1) Have you heard about the Argonne National Laboratory project? If so, can you tell me how you would describe it? What do you think about it? <If not, describe.>
(2) How do you think your community would feel about the node?
(3) How do you think your community could use the data?
(4) What kind of climate data are you most interested in?
(5) Outside of your community, what other stakeholders could benefit from understanding Argonne National Laboratory initiative's data? Why?

- Technology Use

(1) What, if any, social media sites do you use regularly? Do you use Twitter? Instagram? Facebook? TikTok?
(2) Where do you learn about the news? Where do you learn about news and events in your community?
(3) Do you mostly access these sites on a computer or cell phone?
(4) Have you ever engaged in a citizen science project?
(5) Have you used an app like iNaturalist? 311 app? <If part of a community organization> How does <organization> typically compile and share information?
(6) Where is the information stored? Is your organization collecting any climate data?

- Prototype

(1) 1. To what extent do you think real-time alerts about air quality, flooding, heat, or other climate events based on the Argonne National Laboratory node nearest to you would be useful? Would you prefer these via email? Social media? Text?
(2) To what extent do you think monthly summary reports about the climate in your community would be useful? To you? To your organization? Would you prefer these via email?
(3) Imagine there was a weather event like a snow storm or a smokey day and you could send a quick message with a picture or description of this event in your specific location to scientists, would you want to do that? Would you want to share these reports with your community? Would you prefer text, social media, website, app?
(4) Are there other ways it would be useful to see the climate data from Argonne National Laboratory?

- Interview End

(1) Is there anything else I didn't ask about that you'd like to discuss?

Thank you! We really appreciate hearing your thoughts. I'm going to stop the recording now. Could you please fill out this short demographics form? If you know of anyone else who would be interested, please give them my contact information.

Thanks! We will keep you updated on what we learn as the project progresses. Have a good day!

A.4 Community Cafe 1 Survey

Chatham Climate Survey Help us get to know what the main climate needs are in Chatham. This is a collaboration between Greater Chatham Initiative and the University of Chicago. You can view the University of Chicago research consent document here (you will also be provided a copy at the <Date> meeting).

(1) What is your biggest climate/weather concern? Mark only one oval.
    - Air quality
    - Flooding
    - Drought
    - Extreme heat
    - Extreme cold
    - Snow
    - Other:
(2) Why is this your biggest weather/climate concern?
(3) Do you have any health concerns related to weather/climate? Check all that apply.
    - Asthma
    - Mold allergy
    - Heat stroke
    - Mental health
    - Other:
(4) How do you usually check the weather? Check all that apply.
    - Android weather app
    - iPhone weather app
    - AccuWeather
    - National Weather Service / NOAA
    - The Weather Channel
    - Weather Underground
    - Other:
(5) What device do you usually use to check the weather? Check all that apply.
    - Phone
    - Computer
    - TV
    - Radio
    - Smart watch
    - Sensors / thermometer at home
    - I ask a friend or relative
    - Other:
(6) How often do you check the weather? Mark only one oval.
    - Multiple times a day
    - Once a day
    - A couple times a week
    - A couple times a month
    - When there is severe weather
    - I don't check the weather

- Other:

(7) Do you receive 311 text alerts about the weather (a Chicago service)? Mark only one oval.
- Yes
- No

(8) To what extent do you feel the weather report you use is accurate? Mark only one oval.
- 1 Very accurate
- 2
- 3
- 4
- 5 Not accurate

(9) How knowledgeable would you say you are about climate issues?
- 1 Very knowledgeable
- 2
- 3
- 4
- 5 Not knowledgeable

(10) Are there any climate/weather apps or programs you particularly like?

A.5 Community Cafe 1 Demographics Survey

(1) Do you own or rent your home?
- Own
- Rent
- Other:

(2) Have you experienced flooding in the following places?
- Home
- Street
- Office
- Other:

(3) What is your age?
- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65-74
- 75+

(4) What is your highest level of education?
- Less than high school degree
- High school degree
- Associate's / Some college degree
- Bachelor's degree
- Master's degree
- Doctoral degree
- Prefer not to answer

(5) What is your gender?
- Female identifying
- Male identifying
- Non-binary
- Prefer not to answer
- Prefer to self-describe:

(6) Which category best describes you?
- American Indian or Alaska Native
- Asian
- Black or African American
- Hispanic, Latino, or Spanish origin
- Middle Eastern or North African
- Native Hawaiian or Pacific Islander
- White
- Prefer not to answer
- Prefer to self-describe:

(7) What is your zip code?

(8) What is your occupation?

A.6 Community Cafe 1 Facilitator Agenda

Facilitator Agenda <Date>
Facilitator Name:

11:00 – 11:15 Introduction
11:15 – 12:15 Discussion Session 1
- Table Climate Topics (may be duplicate tables of some topics):
  - Air quality
  - Flooding
  - Extreme cold and snow
  - Extreme heat and drought

12:15 – 1:00 Lunch
1:00 – 1:45 Discussion Session 2
- Storyboard session:
  - Same table topics as Discussion 1
  - The University of Chicago research team will describe storyboards and give examples
  - Participants will spend 5 min drawing their own
  - Discussion will follow

1:45 – 2:00 Wrap up

Facilitator Notes - Session 1

- What are some examples of times when [climate issue] was a problem for you?
  - What happened?
  - Did you receive any alerts in advance?
  - What did you do after?
- Who in Chatham is impacted most by [climate issue]?
- What are ways an app could provide information/education or allow for communication or reporting that would be useful in addressing [climate issue]?

Facilitator Notes - Session 2

- 1. What are some of the scenarios you drew in your storyboard?
- What are some of the common themes or ideas that people had when drawing the storyboards?

A.7 Community Cafe 2 Survey

Chatham Climate App Survey

We will email a $15 Amazon gift card to registered Flood Prevention Fair participants filling out this survey. To receive the gift card, you MUST provide the same email that you registered with for the Flood Prevention Fair AND you must fill it out by the end of the Flood Prevention Fair (2pm on <Date>). If you are filling out the paper version you must return it to a University of Chicago research team representative at the Flood Prevention Fair. If you forgot what email address you registered with, you can see a University of Chicago research team representative.

Your Email Address:

(1) Please rank which mockup you prefer (1 to 3 where 1 is best):
- Mockup 1:
- Mockup 2:
- Mockup 3:

(2) Why did you select this ranking?
(3) What would you like to change about the mockups, if anything?
(4) What is your biggest climate/weather concern? (Select one)
- Air quality
- Flooding
- Drought
- Extreme heat
- Extreme cold
- Snow
- Other:

(5) Do you have any health concerns related to weather/climate? (Select all that apply)
- Asthma
- Mold allergy
- Heat stroke
- Mental health
- Other:

(6) How do you usually check the weather? (Select all that apply)
- Phone
- Computer
- TV
- Radio
- Smart watch
- Voice assistant (e.g. Alexa device)
- Sensors / thermometer at home
- I ask a friend or relative
- Other:

(7) Do you receive 311 text alerts about the weather (a Chicago service)?
- Yes
- No

(8) Have you ever used 311 to make a service request (a Chicago service)?
- Yes
- No

(9) If yes, to what extent have you found 311 helpful in resolving your concerns?
- Very helpful
- Somewhat helpful
- Neither helpful nor unhelpful
- Somewhat unhelpful
- Very unhelpful

(10) If 311 was not helpful or you prefer not to use it, please explain why:
(11) Have you ever contacted your alderman about a climate/weather issue?
- Yes
- No

(12) If yes, to what extent have you found contacting your alderman helpful in resolving your concerns?
- Very helpful
- Somewhat helpful
- Neither helpful nor unhelpful
- Somewhat unhelpful
- Very unhelpful

(13) If your alderman was not helpful, please explain why:
(14) Do you own or rent your home?
- Own
- Rent
- Other:

(15) Have you experienced flooding in the following places?
- Home
- Street
- Office
- Other:

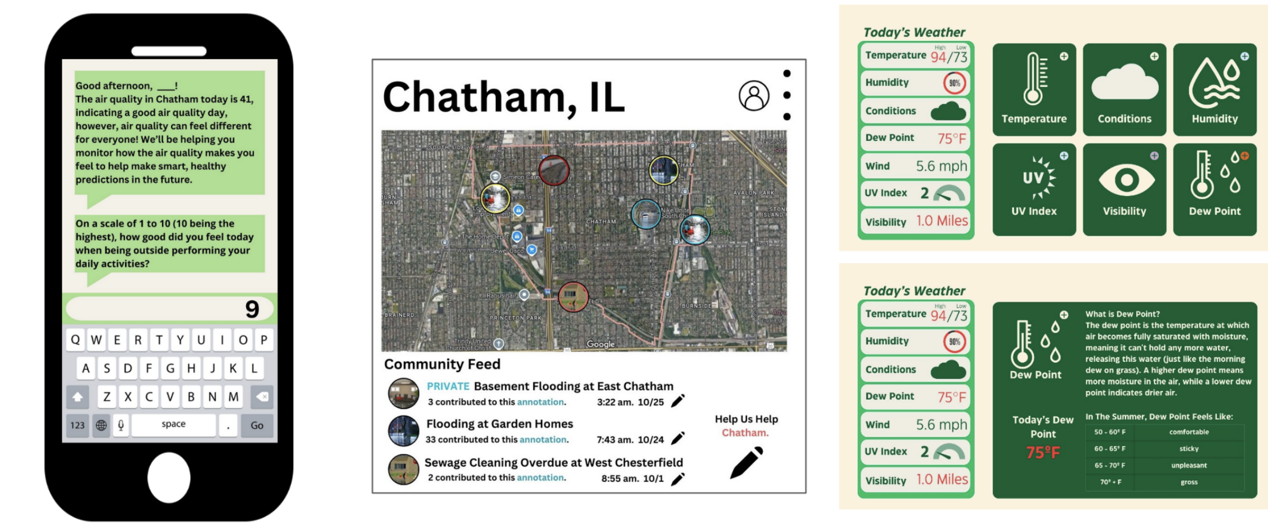
(16) What is your age?
- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65-74
- 75+

(17) What is your highest level of education?
- Less than high school degree
- High school degree
- Associate's / Some college degree
- Bachelor's degree
- Master's degree
- Doctoral degree
- Prefer not to answer

(18) What is your gender?
- Female identifying
- Male identifying
- Non-binary
- Prefer not to answer
- Prefer to self-describe:

(19) Which category best describes you?
- American Indian or Alaska Native
- Asian
- Black or African American
- Hispanic, Latino, or Spanish origin
- Middle Eastern or North African
- Native Hawaiian or Pacific Islander
- White
- Prefer not to answer
- Prefer to self-describe:

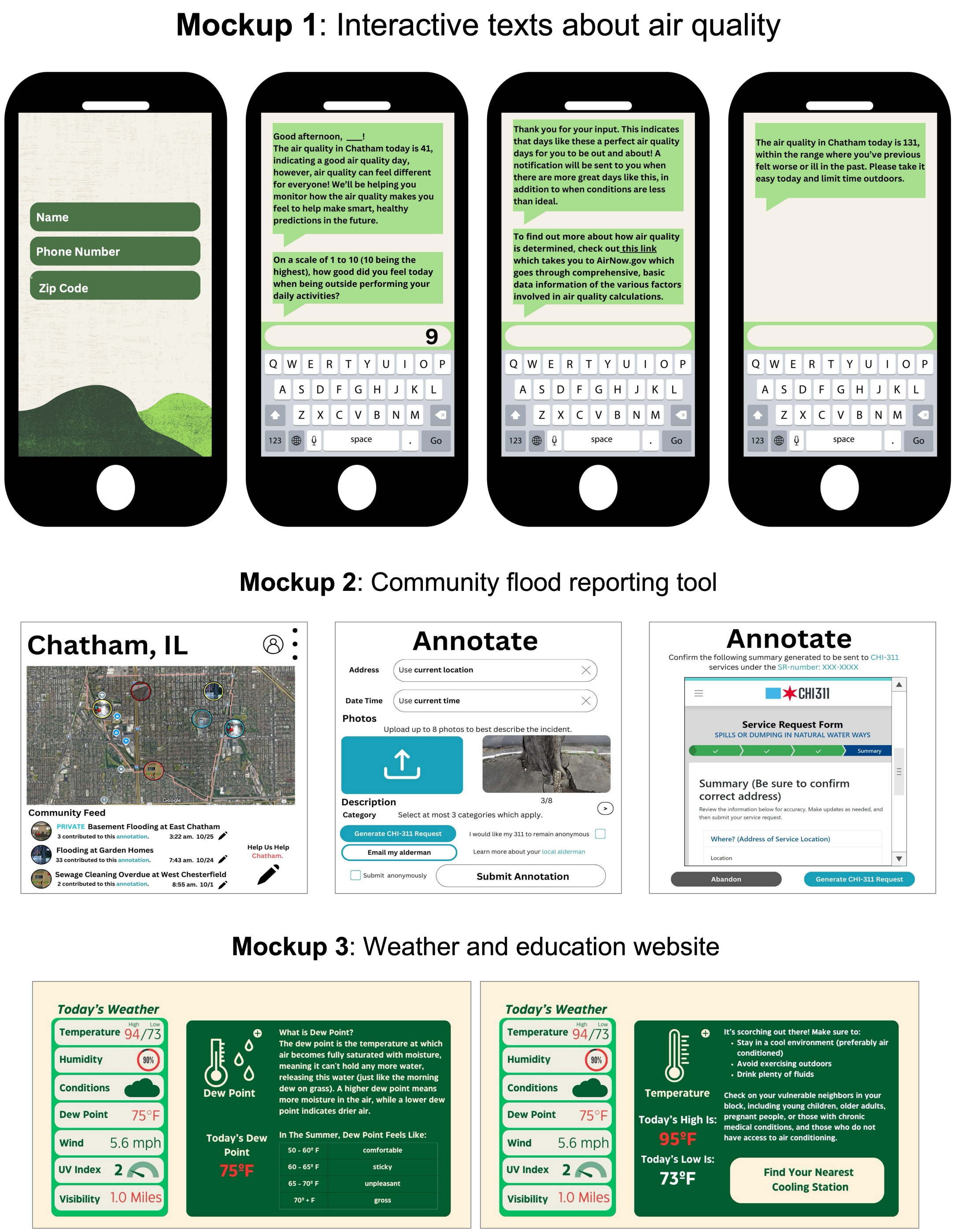
(20) What is your zip code?
(21) What is your occupation?



Mockup 1: Air quality texts **Mockup 2: Flood reports** **Mockup 3: Educational website**

Figure 8

A.8 Community Cafe 2 Mockup Annotation Survey



A.9 Community Cafe 3 Survey

Chatham Flood Reporting App Survey

We will email a $25 Amazon gift card to this email address after the event.
Your Email Address:
Please write any initial feedback/comments you had when testing the app:

(1) A. General questions:
  (a) What device would you prefer to use the flood reporting app on?
    - Mobile phone
    - Computer / laptop
  (b) What should we name the flood reporting app?
    - FloodWatch
    - FloodMap
    - FloodTracker
    - HighWater
    - RippleReports
    - TideTogether
    - Other
  (c) When do you imagine you might use the app? (Check all that apply)
    - During severe weather
    - During spring / rainy season
    - At any time it rains
    - Other:
  (d) Questions about creating a new flood report:
    (i) I found the map interface easy to use.
      - Strongly Agree
      - Agree
      - Neutral
      - Disagree
      - Strongly Disagree
    (ii) I feel comfortable sharing the exact location/address of a flood incident.
      - Strongly Agree
      - Agree
      - Neutral
      - Disagree
      - Strongly Disagree
    (iii) I feel comfortable sharing that my basement flooded with these groups:
      - Neighbors
      - Greater Chatham Initiative
      - Public
      - Science research (not public)
      - Other (please specify)
    (iv) Please see attached "Flood Report Form". These are the questions we'd like to ask when submitting a flood report. Are any of them confusing?
    (v) Do you have any additional feedback on submitting a new flood report?
  (e) Questions about community feed:
    (i) I found the Community Feed showing local flood reports useful.
      - Strongly Agree
      - Agree
      - Neutral
      - Disagree
      - Strongly Disagree
    (ii) Please tell us the reason for your answer above.
    (iii) Do you have any examples of times when you would prefer not to share your flood report in the community feed?
  (f) Questions about connecting to 311 and emailing the alderman:
    (i) Have you ever used 311 to make a service request (a Chicago service)?
      - Yes
      - No
    (ii) If yes, to what extent have you found 311 helpful in resolving your concerns?
      - Very helpful
      - Somewhat helpful
      - Neither helpful nor unhelpful
      - Somewhat unhelpful
      - Very unhelpful
    (iii) If 311 was not helpful, please explain why:
    (iv) I would be interested in submitting flood reports to 311 via the app.
      - Strongly Agree
      - Agree
      - Neutral
      - Disagree
      - Strongly Disagree
    (v) Have you ever contacted your alderman about a climate/weather issue?
      - Yes
      - No
    (vi) If yes, to what extent have you found contacting your alderman helpful in resolving your concerns?
      - Very helpful
      - Somewhat helpful
      - Neither helpful nor unhelpful
      - Somewhat unhelpful
      - Very unhelpful
    (vii) If your alderman was not helpful, please explain why:
    (viii) I would be interested in submitting flood reports to my alderman via the app.
      - Strongly Agree
      - Agree
      - Neutral
      - Disagree
      - Strongly Disagree
  (g) Questions about Resources page:
    (i) What information on the resources page did you find most useful? (See a print out with the full Resources at the end of this packet.)
    (ii) Is there any additional information you would like included on the resources page?

(h) Climate and demographics questions:
   (i) Did you attend the first Community Cafe event about this climate app on <Date>?
      - Yes
      - No
   (ii) Did you attend the session about this climate app at the Chatham Flood Information Fair on <Date>?
      - Yes
      - No
   (iii) How do you usually check the weather? (Select all that apply)
      - Phone
      - Computer
      - TV
      - Radio
      - Smart watch
      - Voice assistant (e.g. Alexa device)
      - Sensors / thermometer at home
      - I ask a friend or relative
      - Other:
   (iv) Do you receive 311 text alerts about the weather (a Chicago service)?
      - Yes
      - No
   (v) Do you own or rent your home?
      - Own
      - Rent
      - Other:
   (vi) Have you experienced flooding in the following places?
      - Home
      - Street
      - Office
      - Other:
   (vii) Do you have a stable internet connection at home?
      - Yes
      - No
   (viii) What is your age?
      - 18-24
      - 25-34
      - 35-44
      - 45-54
      - 55-64
      - 65-74
      - 75+
   (ix) What is your highest level of education?
      - Less than high school degree
      - High school degree
      - Associate's / Some college degree
      - Bachelor's degree
      - Master's degree
      - Doctoral degree
      - Prefer not to answer
   (x) What is your gender?
      - Female identifying
      - Male identifying
      - Non-binary
      - Prefer not to answer
      - Prefer to self-describe:
   (xi) Which category best describes you?
      - American Indian or Alaska Native
      - Asian
      - Black or African American
      - Hispanic, Latino, or Spanish origin
      - Middle Eastern or North African
      - Native Hawaiian or Pacific Islander
      - White
      - Prefer not to answer
      - Prefer to self-describe:
   (xii) Is English the first language you learned?
      - Yes
      - No, first language:
   (xiii) What is your zip code?
   (xiv) What is your occupation?
   (xv) Climate scientists at Argonne National Laboratory will be studying rain/flooding in Chatham this spring. Could we contact you with more information about using the app consistently to report flooding, if any, during <Date>? This reporting campaign will be in collaboration with the science efforts to help Greater Chatham Initiative understand Chatham flooding.
      - Yes
      - No