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The role of living labs in cultivating inclusive and responsible innovation in precision agriculture

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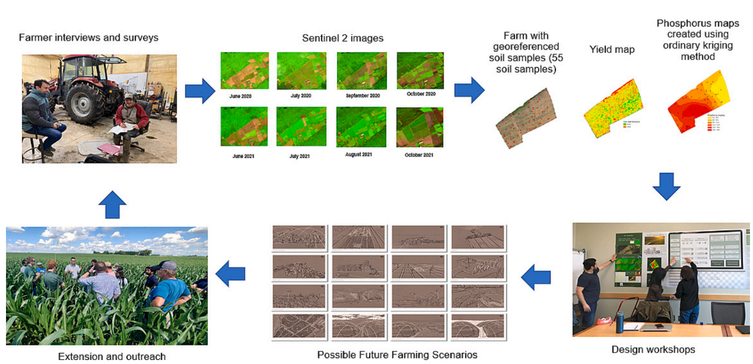
HIGHLIGHTS

- Living Labs emphasize participation and experimentation to address sustainability challenges and foster innovation.
- Farmers' local knowledge about soil, crops, and weather is vital for precision agriculture development and implementation.
- An interdisciplinary approach is essential for responsible precision agriculture development and implementation.
- Collaborative design practices within living labs help make policy making processes more transparent.

GRAPHICAL ABSTRACT



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ABSTRACT

Context: The emergence of precision agriculture technologies has brought forward new opportunities and challenges in the agricultural sector.

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Objective: We delve into the role of living labs as dynamic platforms for fostering responsible innovation in precision agriculture. We highlight our early experiences regarding processes and best practices by which an interdisciplinary research team uses living labs as a methodological approach to design and test trustworthy PA innovation.

Methods: Our living labs methodology is composed of five interrelated activities: (a) face-to-face interviews and surveys with farmers, (b) multidimensional field data collection and analysis, (c) a quasi-field experiment and serious games to test the effectiveness of sensor-driven performance-based payment for improving ecosystem services, (d) design workshops, and (e) extension and outreach of PA tools and knowledge to farmers and rural communities.

Results and conclusions: Our initial findings demonstrate how living labs can be leveraged to co-create sustainable solutions that are socially and economically responsive to the challenges of farmers and rural communities, and environmentally sustainable. Our research underscores the importance of including experts from various fields to collaborate and contribute to innovation development.

Significance: We share the challenges and opportunities associated with implementing living labs in the context of precision agriculture technologies. By sharing our early experiences in establishing living labs in the United States, we aim to contribute to the promotion of inclusive and responsible innovation within the living lab community and offer valuable guidance to other researchers embarking on similar initiatives.

1. Introduction

Precision agriculture (PA) stands at the intersection of human-technology collaboration, harnessing data-driven agricultural techniques and localized farm data to provide farm-specific recommendations (Klerkx et al., 2019; Rossel and Bouma, 2016). Driven by digital technologies such as artificial intelligence (AI) and machine learning (ML), PA innovations have the potential to revolutionize farming practices, enhance crop yields, and mitigate environmental impacts. Yet, several challenges remain unresolved that also impede farmers' adoption of PA (Gardezi et al., 2023; Gardezi et al., 2022; Gardezi and Stock, 2021). These include questions such as how to convert big data into improved farm management decisions (Lowenberg-DeBoer and Erickson, 2019), how to use PA to help optimize resources to limit environmental impacts of farming (Tey and Brindal, 2012), and how best to train the future workforce and overcome barriers such as economic and opportunity costs (Gardezi and Bronson, 2020), and social-psychological barriers such as negative perceptions or attitudes associated with these burgeoning technologies (Mizik, 2023). This paper represents our initial exploration of living laboratories or "living labs" (LLs) as a methodological approach to co-design PA tools that can enhance farmer trust, improve farm productivity, and promote environmental sustainability.

Traditional policy interventions such as research and development (R&D) investments or subsidies are insufficient on their own for initiating and fostering sustainability transitions (Kuhlmann and Rip, 2018). Recently, LLs have gained attention as a specific type of intervention that enables stakeholders to co-design, test, and learn from socio-technical innovations in real-time and over the longer term (Dell'Era and Landoni, 2014). There is clear value in introducing LLs to the fore as means of inclusion and trust-building in responsible innovation (RI). Building trust with stakeholders across the food system value chain, such as farmers, requires sustained and continuous engagement efforts, where social and environmental sensing can help co-design and co-develop new technologies (Guzman et al., 2008; Zavratnik et al., 2019). This comment submitted to the special issue on "*Enabling Inclusive Innovation in Agriculture and Food Systems*" highlights our early experiences regarding processes and best practices by which an interdisciplinary research team uses LLs as a methodological approach to design and test trustworthy PA innovation. By sharing these methodological experiences of setting up LLs in the US, we hope that these reflections will forward the LL agenda of RI and guide fellow researchers in their endeavors.

2. Living labs for responsible innovation

RI goes beyond viewing farmers and other stakeholders across the food system value chain as mere recipients of new technologies (Klerkx and Rose, 2020; Fielke et al., 2022; Prutzer et al., 2023). Instead, it acknowledges their pivotal role in actively shaping a collective future of science and technology. LLs offer a promising approach to bridge the science-policy-society gap (Bronson et al., 2021). It is worth mentioning that LLs are not entirely new and co-creating and testing solutions with active community engagement has a long history in social sciences, specifically in the field of participatory action research (PAR) (Lewin, 1946). LLs can be understood to build upon and extend the traditions of PAR, specifically by leveraging community involvement and co-design processes to address complex social and technical challenges (Ahmadi et al., 2018; Logghe and Schuurman, 2017). In the case of our ongoing investigation, we are conceptualizing LLs as dynamic spaces where innovation is not confined to laboratories but tested and refined in the real-world, specifically at the farm-level. With the goal of pursuing user-centered designs of PA tools, LLs provided a collaborative platform to our project team to co-create with farmers and prototype digital agriculture technologies while considering diverse perspectives and environmental sustainability.

In this section, we outline our living lab methodology as an approach at this preliminary stage to learn and co-create knowledge and tools with farmers in South Dakota (SD), Vermont (VT), and Virginia (VA). Farms in these three US states represent different farming systems and workforce dynamics ranging from medium to large-scale farms in SD state (~500–10,000 acres) whereas VT and VA are dominated by small and medium scale farms (~15–150 acres). Furthermore, each of the three states produces a vast range of agricultural commodities. For instance, in SD, the most essential agricultural products are corn, soybeans, wheat, livestock, and ethanol (Joshi et al., 2019). VT farms typically specialize in niche products such as dairy, hay and maple syrup, whereas VA is one of the most diverse agricultural commodity producers in the country, producing commodities rated in the top 10 among all U.S. states, such as leaf tobacco (ranked third) and peanuts (ranked ninth) (VA Agriculture, 2019). Regarding employment, the agriculture sector accounts for 30%, 3.6% and 9% of all the jobs in SD, VA and VT respectively (USDA, 2022; NOFA Vermont, 2022; VA Agriculture, 2019; USDA, 2012). SD and VT are among the top 15 states in the US whose economies are "most dependent" on agriculture (Farm Bureau, 2019).

In our initiative to harness LLs for RI in PA, we employ an iterative process of PA development that aims to inspire developers to create user-centered and socially acceptable products and tools. At this early stage, we have observed that incorporating perspectives of farmers who are affected by new technological development enhances perceptions of trustworthiness and improves attitudes. Moreover, technology developers can use LLs to demonstrate a willingness to adopt technologies and policies, and thus take the interests of farmers into consideration (Eastwood et al., 2022; Ditzler et al., 2018). Our living lab methodology aims to provide valuable insights into how iterative engagement with stakeholders can drive RI, sustainability, and trust in PA. As part of our preliminary investigation, Fig. 1 summarizes our living lab methodology, which is composed of five interrelated and ongoing activities: (a) face-to-face interviews and surveys with farmers, (b) multidimensional field data collection and analysis, (c) a quasi-field experiment and serious games to test the effectiveness of sensor-driven performance-based payment for improving ecosystem services, (d) design workshops, and (e) extension and outreach of PA tools and knowledge to farmers and rural communities. Prior to beginning this research, we obtained internal review board (IRB) approval to carry out the study. Our LLs methodology involves several key components. (See Fig. 2.)

2.1. Conducting in-depth and face-to-face farmer interviews

To gain insights into the specific needs, challenges, and aspirations of farmers, we conducted in-depth and in-person interviews and surveys. Qualitative techniques, including interviews, are valuable for understanding local perspectives and contextual influences on farmer's decision making. We recruited farmers using new as well as existing farmer collaboration networks. A balanced representation of farmers across various age groups, education and technological literacy, farm size, and state of adoption of PA tools was sought. Farmers that produced a variety of agricultural commodities such as corn, soybeans, dairy, livestock, alfalfa, and hay were interviewed. These interviews aimed to gauge farmers' attitudes and perspectives on various issues, including their level of trust in various technologies such as sensors, AI-driven models, the efficacy of recommendations from existing hydrological models (such as the Agricultural Policy / Environmental eXtender (APEX) model), their approaches to modifying their farm production systems in response to economic and environmental pressures, and the effectiveness of relevant subsidies on farm productivity and environmental footprint. Region-specific questions focusing on issues pertaining to South Dakota, Vermont, and Virginia were also included in the interview.

2.2. Converting data collected from multispectral sensors, satellite imagery, field monitors, and in-situ soil sensors into useable information for farmers

Agriculture is a multidimensional field of study, and its proper understanding requires diverse agroclimatic data. To enhance our understanding about agricultural systems and issues related to it, we identified fields that were of particular interest to farmers due to their agronomic properties, such as soil fertility and yield potential, as well as the challenges encountered by farmers in cultivating crops within those areas. After field identification, we have been using multidimensional field data collection including high-frequency satellite, UAV imageries, soil nutrient and water quality testing. Moreover, in a subset of farms where pre-existing water quality monitoring infrastructure and baseline nutrient export data were available, a robust water sampling program is also in progress. Following data collection using various sensors and monitoring systems, we have been developing novel deep learning and AI-based algorithms to convert these data into useful information, such as the prediction of farm-level nutrient flux, greenhouse gas (GHG) emissions or carbon footprint of agricultural systems, and crop yield. For example, we utilized a combination of AI algorithms and high-resolution satellite images to predict soybean yield at different growth stages (Joshi et al., 2023). Similarly, we deployed sensors and used ML models to predict daily CO2 and N2O emission from cover cropping systems by combining sensor collected data with meteorological information such as soil moisture/temperature, air temperature, and total rainfall (Joshi et al., 2022). ML model results can be used to help determine the total carbon budget of conservation agricultural management systems, and thus assist in management decisions such as planting cover crops. Additionally, our approach at this preliminary stage involves utilizing these multidimensional data to calibrate and validate the farm-scale Agricultural Policy/Environmental eXtender (APEX) model (Wang et al., 2012) across the LLs, and assess farmers' interest in these model forecasts. This work is currently in progress, but we expect these models to play a crucial role in predicting the dynamics of phosphorus (P), nitrogen (N), water budgets and soil organic carbon (SOM), and crop yield on the farm. To address concerns regarding data security and privacy, we are employing standard information security techniques, including encrypted communication and data access control, ensuring the secure collection, storage, processing, and access of agricultural microdata.

2.3. Using alternative sensor-driven "pay-for-performance" strategies to incentivize farmer innovation and behavioral change towards environmental sustainability

While there is a long history of paying and/or subsidizing farmers for conservation practices, there have been limitations on monitoring the actual effects of these practices on the environment. For example,

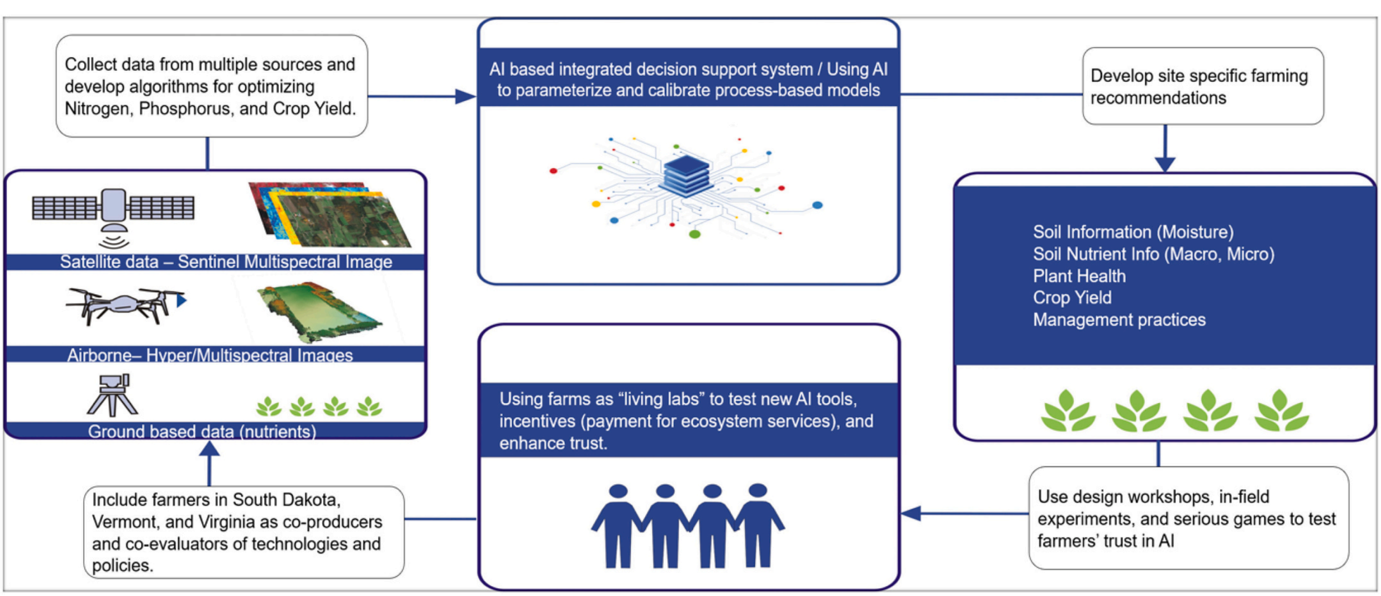

Fig. 1. Overall living lab methodology (Source: Authors' own).

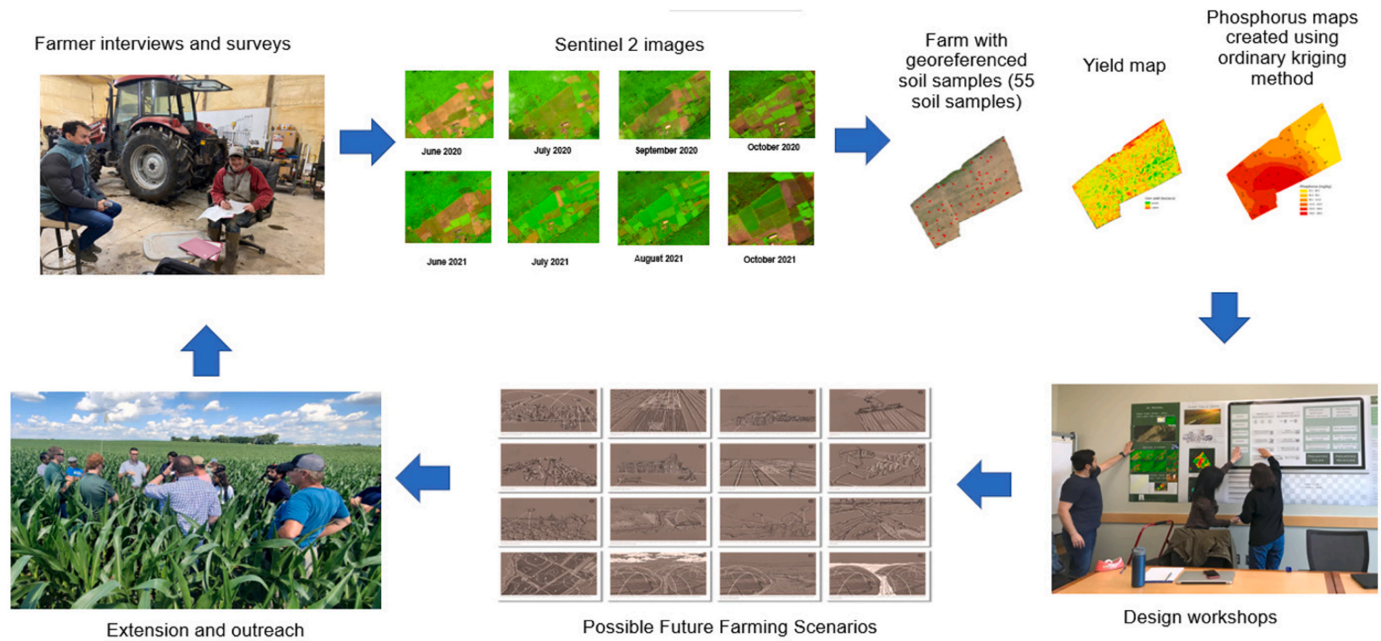

Fig. 2. Living labs for responsible innovation in precision agriculture. (Source: Authors' own).

environmental systems are influenced by numerous variables, including weather patterns, soil conditions, and vegetation patterns, which makes it challenging to isolate the specific impact of a single conservation practice on outcomes, such as nutrient runoff reduction. Alternative "pay-for-performance" strategies, which rely on innovative sensor/PA technologies and data modeling, have been promoted as approaches that permit more cost-effective decision-making and incentivize farmer innovation and behavioral change towards environmental sustainability (Lau, 2013; Sone et al., 2019; Wu et al., 2017; Zia et al., 2020). While formal results are pending, our initial interviews with farmers, we were able to identify the most appropriate fields/sites within their farms that will be monitored through aerial and ground-based soil sensors. Early findings identified varying interests among farmers that extend beyond simply maximizing crop yield, for example, emphasizing soil health and prioritizing water quality. Consequently, we organized our LLs into three distinct categories aligned with these preferences, facilitating a more precise and tailored co-design approach. Using the living lab methodology, our early experiences shed light on testing whether performance-based payment for ecosystem services (PES) mechanisms, compared with a control group of extant policy mechanisms, increase farmer productivity and enhance environmental sustainability. Farmers have multiple fields enrolled in the experiment and will receive either information, payments tied to performance or the combination of payments and information on individual fields.

For fields in the control group, farmers are provided information in the form of a traditional APEX model. They are given baseline monetary incentives to participate in the experiment. Farmers with fields in the first treatment group are provided information from an enhanced APEX model that uses AI to parameterize and calibrate the existing APEX model. For their fields in this group, farmers receive baseline payments only. Another group of fields were placed in the second treatment group, where the farmers are paid performance-based payments on a sliding scale, i.e. for reductions in P or N pollution compared with the baseline period. For the fields in this second treatment group, farmers receive information only in the form of the traditional APEX model. The third treatment group constitutes farmers who receive performance-based payments (as in the case of the second treatment group) and information to utilize the new enhanced APEX model (as in the case of the first treatment group). This is an example of a 2 × 2 factorial design, which in our case, comprises corn/soybean, pasture-based dairy and cattle, and alfalfa/hay farms in the three US states. This experiment (still in progress) constitutes a rigorous and comprehensive approach to data collection, analysis, and algorithm development, enabling us to advance our understanding of PA and environmental monitoring while addressing critical challenges in the field.

We utilize a serious game, a form of simulation-based experiment, to recreate environments that demand critical decision-making dynamics. This approach enables us to gather data for testing the aspects of the real-world 2 × 2 factorial design quasi-experiment mentioned earlier. Our objective is to investigate farmer behavior within a simulated agricultural setting and identify factors influencing gameplay through post-game surveys. One significant advantage of simulation is our ability to control contextual and treatment variables. For instance, by compressing time compared to real-world conditions, we can simulate multiple growing seasons within a single experiment. This not only facilitates iterative learning but also provides a platform for envisioning the future. Participants are rewarded with a portion of real-world currency based on their in-game earnings, motivating them to optimize their perceived utility, such as maximizing profit, minimizing costs, or managing uncertainty. Through simulating agronomic dynamics in our game, we can uncover trade-offs between economic profitability and ecological costs while assessing socio-psychological determinants of PA adoption. Our simulation-based experiment specifically examines dimensions of trust in PA, particularly in relation to the accuracy and precision of recommendations from three different information sources for agronomic decisions. By comparing (a) human-generated recommendations with those derived from (b) simple mathematical models and (c) AI-based recommendations for fertilizer application rates and projected net returns, we have begun to explore issues related to trust, attitudes towards AI and computer-generated forecasts, incentive structures, funding sources (public, private, and compliance markets), and willingness-to-pay. Through conclusive results are forthcoming, deploying this serious game to a diverse group of participants, including living lab participants, crop advisors, and the general public, will yield insights into generalizable preferences for trust in new and emerging technologies in agriculture.

2.4. Administering design workshops to envision future scenarios and develop low-fidelity prototypes

Collaborative design workshops play a critical role in involving farmer perspectives, values and interests in envisioning (and ultimately shaping) the diverse future scenarios of farms, as well as the broader agricultural landscape. Design workshops and materials create a liminal space for creative thinking, open dialogue, inviting critical and thoughtful consideration for how AI and ML might practically impact farmers, farms and rural communities. In concert with the RI principles, "designerly" approaches (Cross, 1982), particularly those oriented towards participation (Brandt et al., 2012) and speculation (Auger, 2013; Dunne and Raby, 2013; Sterling, 2005), provide farmers with a sandbox to explore alternative realities; mapping out the political, material, and infrastructural implications and trajectories of using possibly disruptive emerging technologies in agriculture. Our design workshops were informed by preliminary data collection of farmers over the period of one year in the form of interviews and surveys. The design workshop aimed to investigate how can we collaboratively design decision support tools (DSTs) with farmers, for use in climate smart agriculture. This involved three key stages (1) Decision Mapping (2) Scenario Building, and (3) Requirements Gathering.

2.4.1. Decision mapping

The decision mapping exercise involved understanding the process of nutrient-related decision-making by the farmers (e.g., how much fertilizer to use). We were interested in exploring how farmers identify and organize their decisions across a temporal scale, as well as highlighting the dimension of importance. We used a graphical 2-x-2 matrix tool (Hasso Plattner Institute of Design at Stanford, n.d.) to graph different dimensions of key decisions across a temporal scale in a one-on-one activity. Farmers first listed key decisions important for nutrient management using sticky notes, and then placed them in order of priority to reveal key areas of importance. Thereafter farmers engaged in a focused discussion with facilitators (a transdisciplinary team of researchers) — to deep dive into the process of decision making in the farming landscape, identifying regional and crop-specific problems associated with farmers' decision making.

2.4.2. Scenario building

After the mapping exercise, farmers were involved in speculating over different scenarios of farming technologies in near future settings. This involved introducing farmers to visions of future farms, as well as a design fiction prototype — The New Farm Times, a newspaper styled photovisual article (presented using Figma) with headlines of articles, serving as provocations illustrating possible futures. The photo essay comprised of sixteen carefully crafted images, that drew upon farmer insights during the pre-work (i.e., interviews, surveys, desk research) — depicting possible speculative futures of digitally enabled farming technologies and systems. These images were hand drawn illustrations (using Procreate), coupled with a caption describing the image. The images were used as a hybrid photo elicitation-card sorting technique, using a preconfigured Q-methodology analytical approach towards the card sort. Farmers were asked to sort images in order of likelihood on a Q-methodology template board discussing their rationale with the research team. Farmers were also asked to react and discuss their responses to the newspaper headlines where we shared hypothetical news reports from the future of farming in the US, in which farmers were able to achieve their nutrient management goals in a sustainable way. Farmers were asked how the realization of these goals could have been made possible in the future.

2.4.3. Requirements gathering

The final exercise of the workshop involved farmers being given a short presentation on two existing models of DSTs, an AI-based model and a process-based model (APEX). Farmers were asked to comment on their experiences of using these models in the past. They were then asked to suggest what features of these tools they like or dislike the most, and how they would like to improve or completely replace the existing interfaces portraying the results of these models. This exercise was followed by a focus group between the project team members and the farmers.

2.5. Outreach and engagement

Communication is vital in facilitating RI. We actively engage with broader farmer audiences to convey the challenges and opportunities presented by AI and ML in agriculture. This dialogue encourages knowledge sharing and empowers farmers to participate actively in shaping the future of farming. As part of our dissemination workshops, living lab farmers were presented with site-specific, spatial improved images of soil parameters (i.e., improved maps using observed data on pH, soil phosphorus, and soil organic matter from individual farms) in addition to the field averaged values currently used as input to the APEX models. We are also leading several PA hackathons to simultaneously educate youth on agricultural management by developing a serious game. This application of practical knowledge enabled middle and high school aged children to immerse themselves in the challenges of farm management while learning both to write and execute computer code and bolster communication skills around the complex topic. The overarching goal of the hackathon was to educate and demonstrate the risks and benefits of PA technologies. Students learned to code in the Unity gaming platform to communicate the benefits and challenges associated with PA applications in farming.

3. Opportunities for living labs to drive inclusive and responsible innovation

3.1. Empowering farmer-centered innovation through LLs in PA

Participatory action research (PAR) has significantly influenced the development of LLs, with its focus on active community engagement, collaboration, and iterative learning and implementation (Reason and Bradbury, 2008). PAR principles have provided a foundational framework for LLs to co-create and test innovative solutions with real-world contexts (Bergvall-Kareborn and Stahlbrost, 2009) and evolve as a dynamic space for inclusive and responsible innovation (Almirall and Wareham, 2008). Although our work is currently ongoing, we have found LLs to be a useful approach emphasizing participation, experimentation, and learning while also recognizing the significance of farmers' situated knowledge in addressing sustainability challenges and facilitating inclusive and responsible innovation. While LLs can influence the development of new practices and reshape relationships between individuals and their local and place-specific environments (Toffolini et al., 2021; Gamache et al., 2020), inclusive innovation underscores the significance of social organization, representation, and incentives in fostering a genuine participatory innovation process that is rooted in local demand and context (Swaans et al., 2014). Inclusive innovation provides guiding principles and heuristics that specially attend to the characteristics of innovation, including how actors and organizations come to engage in learning, and the institutional rules that shape their actions (Opola et al., 2021; Foster and Heeks, 2013). Our research takes its inspiration from LLs and current work on inclusive innovation to move beyond imagining and prescribing users, user needs, and use cases in more bounded settings, and instead open up the development process to users themselves in everyday contexts of use. Therefore, we postulate—based on our initial observations—that LLs can assist in sustainability transitions as farmers and other stakeholders seek innovative and inclusive solutions for agricultural, food, environmental, and social concerns through the facilitation of new organizational models that formalize the provision of goods and services (Chataway et al., 2014).

Our early experiences underscore meaningful and diverse user participation in LLs. However, we recognize that these opportunities for participation can be challenging, as it requires overcoming geographical, cultural, and technological barriers. There is an immediate imperative to adopt a fundamentally different approach to innovating in PA, one that is community-centered and integrates diverse forms of knowledge alongside local assessments of socio-environmental risks and benefits. Historically, the development of agricultural technologies has often overlooked or superficially engaged farmers as active participants in the design, implementation, and education processes. When knowledge and technologies are exclusively crafted by accredited experts such as engineers and scientists, they tend to disregard critical contextual considerations that can result in adverse impacts on technology adoption and its socio-environmental consequences. Recent design thinking approaches in agriculture have supported farmers, farm advisors, research scientists, application developers, and policy makers in articulating and involvement in the creation of agricultural technology (e.g., geotagging photo application) that allow technology developers to leverage diverse forms of knowledge and expertise, and thereby increasing the social acceptance of new tools (Kenny et al., 2021). We draw inspiration from this design research and emphasize that agriculture is inherently site-specific, intertwined with the specific cultural and ecological contexts of the regions it serves.

Our preliminary work highlights the significance of local contexts, a multitude of perspectives, and the influence of social power dynamics in comprehending and responding to the repercussions of climate change at the community level. Farmers and other stakeholders (e.g., crop advisors) possess a wealth of knowledge about their environment. This knowledge encompasses various aspects, including local insights into soil, crops, livestock, weather, and climate. This valuable knowledge has been honed and refined over generations. Harnessing this local knowledge and expertise is of particular importance when developing and implementing PA. Our focus on RI vis-à-vis early engagement with farmers to co-develop solutions tailored to their specific challenges helps us initiate discussions about robust and equitable governance structures to ensure sustainability and continued impact.

3.2. Promoting interdisciplinary collaboration in LLs for PA

Our team perceives PA as a socio-technical system, comprising interconnected human actors, institutions (such as knowledge, user practices, cultural values, markets, and policies), as well as non-human elements, encompassing living entities (e.g., crops, livestock), and material objects (e.g., machine learning, AI, the Internet of Things, and robotics) (Geels, 2005; Pigford et al., 2018). This systemic approach underscores the interrelatedness of social, ecological, and technological components, emphasizing that they cannot be examined in isolation but must be comprehended as interconnected systems. We found that a living lab methodology that actively seeks to inclusively and responsibly integrate PA technologies with future agricultural practices and workers by fostering synergy in knowledge, approaches, and viewpoints across various disciplines and sectors can be truly participatory and convergent in its approach. We achieved this integration through several means. Firstly, our team represents a diverse array of disciplines, including Agronomy, Agriculture and Biosystem Engineering, Computer Science, Electrical Engineering, Environmental Engineering, Economics, Plant and Soil Sciences, Public Policy, Sociology, Spatial Sciences, and Statistics. Among the team, there is a shared research focus on investigating the human and social dimensions of agricultural technology and innovation. This shared research interest, spanning multiple disciplines, provides a valuable foundation for leveraging diverse approaches and perspectives to enhance technology research and workforce training.

Effective collaboration across various disciplines is paramount for the success of LLs. Bridging the gap among technology developers, social scientists, and farmers can be a complex endeavor. This is particularly challenging in the context of monitoring and evaluating effectiveness of LLs across different context (Potters et al., 2022). Existing literature on team science and knowledge integration in various research programs and interdisciplinary collaborations provides valuable insights into the integration of expertise across social and natural sciences disciplines (e.g., Stokols et al., 2008). Social sciences, in particular, serve as a crucial bridge connecting the natural sciences, science communication, and policy development. For instance, our design workshop provides opportunities for experts from diverse disciplines to collaborate and contribute to the development of innovations. Engaging multiple stakeholder viewpoints and perspectives, co-creation in design helps in not only bringing objectivity into the design concepts, but also reduces asymmetry of knowledge, by allowing different experts to share their diverse views, and negotiate their way to a consensus (Rittel, 1984) to create collective value (Khan, 2022) by democratizing innovation (Björgvinsson et al., 2010). This democratization of the innovation process turn adds rigor to the 'process' of design (Cross, 2001), and enables participants to better communicate ideas and concerns, critically assess the concepts, and reduces the likelihood of rejection when innovations are eventually rolled out (Björgvinsson et al., 2010). Within farming, collaborative design practices can be used to redesign farming systems by involving farmers in the knowledge production and design-creation processes, reducing the gap between ideation and execution (Lacombe et al., 2018). This work-in-progress highlights the need for further investigation into how LLs can foster collaboration, data-driven decision-making, and open dialogue among stakeholders. While challenges exist, the potential for inclusive, sustainable, and farmer-centric innovation makes LLs a valuable tool in shaping the future of agriculture.

CRediT authorship contribution statement

Maaz Gardezi: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Halimeh Abuayyash:** Writing – review & editing. **Paul R. Adler:** Writing – review & editing. **Juan P. Alvez:** Writing – review & editing. **Rubaina Anjum:** Writing – review & editing. **Appala Raju Badireddy:** Writing – review & editing. **Skye Brugler:** Writing – review & editing. **Pablo Carcamo:** Writing – review & editing. **David Clay:** Funding acquisition, Writing – review & editing. **Ali Dadkhah:** Writing – review & editing. **Mary Emery:** Writing – review & editing. **Joshua W. Faulkner:** Writing – review & editing. **Bhavna Joshi:** Writing – review & editing. **Deepak R. Joshi:** Writing – review & editing. **Awais Hameed Khan:** Writing – review & editing. **Christopher Koliba:** Writing – review & editing. **Sheetal Kumari:** Writing – review & editing. **John McMaine:** Funding acquisition, Writing – review & editing. **Shreya Mitra:** Writing – review & editing. **Sardorbek Musayev:** Writing – review & editing, Visualization. **Panagiotis D. Oikonomou:** Writing – review & editing. **George Pinder:** Writing – review & editing. **Edward Prutzer:** Writing – review & editing. **Jitender Rathore:** Writing – review & editing. **Taylor Ricketts:** Writing – review & editing. **Donna M. Rizzo:** Funding acquisition, Writing – review & editing. **Benjamin E.K. Ryan:** Writing – review & editing. **Maryam Sahraei:** Writing – review & editing. **Andrew W. Schroth:** Writing – review & editing. **Scott Turnbull:** Writing – review & editing. **Asim Zia:** Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Maaz Gardezi reports financial support was provided by National Science Foundation and by National Institute of Food and Agriculture.

Data availability

No data was used for the research described in the article.

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