Big Data: Usage and Application of Big Data in the Human Dimensions of Agricultural & Natural Resources (ANR)

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The role of Extension in U.S. land-grant systems is to disseminate information and scholarship to the public and agricultural stakeholders. When new science and innovations become available, Extension acts as a liaison for making technology understandable and accessible so their stakeholders can reap the benefits (Xu et al., 2023). In the digital era, technology is rapidly evolving, with new innovations consistently being released to continue advancing production and sustainable practices in agricultural and natural resources (ANR). A primary area of growth in ANR is in artificial intelligence (AI) development. Many researchers are focusing on leveraging this technology for the benefit of agricultural producers—increasing global food security (Kesari, 2024; Liu, 2020; Shekhar et al., 2017) and advancing progress toward the United Nations (UN) Sustainable Development Goals (International Telecommunication Union, 2021). These technological advancements are aimed at using science to tackle complex issues related to almost every facet of our lives and the ANR industry. While many of the technologies may be AI driven, these require big data to train machines and create algorithms that leverage this information to produce informed decisions and generate predictions for application (Maaroof, 2015).

And even as many ANR scientists are working to produce these technologies, questions remain on the role of social scientists. While it may be clear how social scientists can assist in evaluation and the creation of innovation-adoption plans, improving data literacy among ANR social scientists is needed to advance their role in other components of AI and big data applications. Additionally, exploration of opportunities for big data usage to support ANR social scientist research, extension, and educational practices is needed to continue progressing this work. The UN Committee of Experts on Big Data and Data Science (UN-CEBD) was formed to explore applications of big data, which include those related to monitoring and reporting on the SDGs (UN-CEBD, 2025). A global data research network was also created in 2015, the Sustainable Development Solutions Network (SDSN) Thematic Research Network on Data Statistics (TReNDS) to continue exploring opportunities for using various data sources for generating solutions and advancing policy (TReNDS, n.d.). From an international development perspective, expanding the knowledge—big data literacy—of those working globally in Extension can continue to advance practices related agricultural production and food security through the integration of big data for innovative solutions. In this philosophical paper, we aim to provide insight into how ANR social scientists can use big data to advance, guide, and support their research, extension, and education practices. We will include an overview of big data, types of data, the big data ecosystem, and opportunities and challenges related to using big data. Further, we address the ethical considerations and social implications of big data usage while emphasizing responsible data stewardship and the need for increased data literacy.

What is Big Data?

Big data is "a collection of data sources, technologies and methodologies that have emerged from, and to exploit the exponential growth in data creation" (Maaroof, 2015, p. 11). Big data is often characterized by three main dimensions––volume, velocity, and variety—referred to as the 3Vs (Khan et al., 2018). Volume refers to the massive amount of data and velocity highlights the rapid speed in which data is produced and analyzed (Gandomi & Haider, 2015). Variety encompasses the different types of data (Gandomi & Haider, 2015). While authors have reported other data characteristics with varying models of "Vs" (Liao et al., 2014: Shah et al., 2015; Sivarajah et al., 2017), the 3Vs are included in all of these models.

TReNDS (2021) reports 10Vs for classifying big data adding volatility, veracity, validity, value, variability, vulnerability, and visualization to the 3Vs. Volatility represents the evolving technology and data storage methods (Cite TReNDS?). Veracity is the trustworthiness of the availability and where the data was derived from while validity is the quality, accuracy, and reliability of the data (TReNDS, 2021). Value encompasses the business value and variability refers to the consistently changing meaning of data (TReNDS, 2021). Vulnerability represents the personal nature and need for privacy, while visualization includes scalability and functionality (TReNDS, 2021). While these additional Vs may not all help determine whether data is *big* data, they are all distinguishing attributes that should be considered when using big data.

Types of Big Data

The term big data refers to the enormous amount of both structured and unstructured data that is derived from technology and software techniques and stored in databases (Maaroof, 2015). There are three primary types of data which include structured, semi-structured, and unstructured data. Structured data has a defined length and amount including both machine-generated data (e.g., sensor, web log, and point of sale data) and human-generated data (e.g., data one inputs in a computer, clickstream data, and gaming-related data) (Maaroof, 2015). Unstructured data does not have defined or consistent fields and may not even include numbers or text. Machine-generated unstructured data can include satellite images, scientific data, photographs, videos, radar, and sonar data (Maaroof, 2015). Human-generated unstructured data includes mobile and voice data, web behavior and content, image and video data, and machine data (Maaroof, 2015). Semi-structured data is commonly derived from social media, blogs, and publicly available websites and includes both structured and unstructured components (Maaroof, 2015).

The UN Statistical Commission (2014) classifies big data as administrative, commercial, sensor, tracking or mobile, and behavioral and opinion data. Administrative data is generated through a program such as medical, insurance, or bank records (TReNDS, 2021). Commercial data includes transactional sources such as those from online or financial transactions or scanners. Sensor data is derived from sensors such as satellites or climate, light, gas, and chemical sensors. Tracking or mobile data includes those generated from mobile devices or global positioning systems (GPS). Behavioral and opinion data includes online searches or opinion-based responses online such as social media posts or comments (TReNDS, 2021). All these data types can be used in the development process and for predicting adoption of new ANR technologies and innovations aimed at responding to complex issues, such as those outlined in the SDGs.

Key Terms Relating to the Big Data Revolution

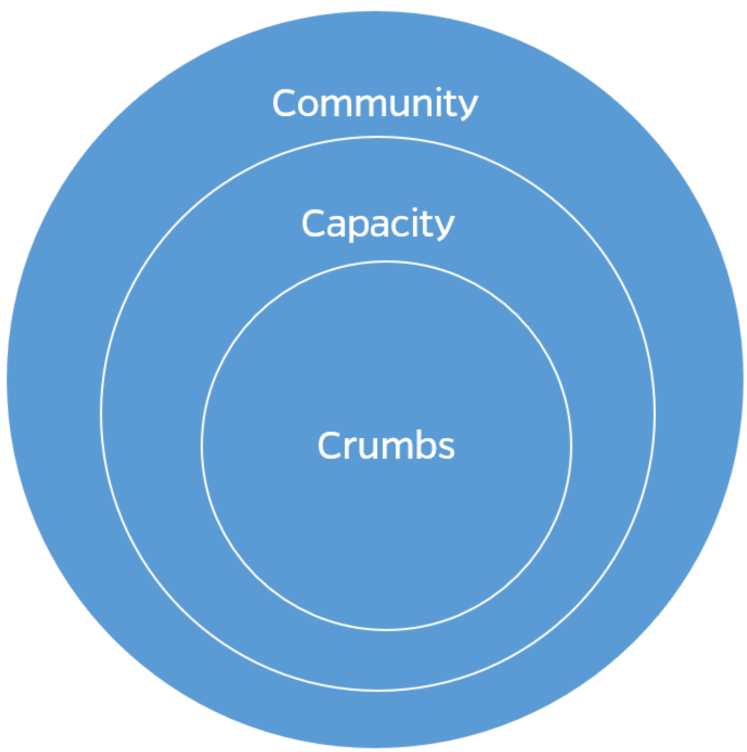
When thinking about big data, it is imperative to consider how big data is used in the big data revolution and related key terms. Applications of big data include AI, machine learning (ML), and the internet of things (IoT). AI uses algorithms from data to perform assigned tasks by mimicking human thinking to solve complex problems (Javaid et al., 2023). ML is a subset of AI (Jha et al., 2019). Most AI is ML, which teaches a machine how to complete an assigned task and produce an outcome through pattern identification (Santra et al., 2021) using structured and semi-structured data. The internet of things is defined as "an embedded system with sensors, software, actuators, electronics and computer to connect and exchange data" (Santra et al., 2021, p. 55). In agriculture, the IoT describes the network of physical elements like animals, plants, environmental factors, and production tools within the agricultural system that use agricultural information sensing devices to exchange and communication information across the internet (Xu et al., 2022). An understanding of these general terms and applications provides a basis for considering how big data exists in the big data ecosystem and the ways it can be harnessed to advanced ANR technology.

The Big Data Ecosystem

The big data ecosystem (see Figure 1) is “the comprehension of massive functional components with various enabling tools” (Cui et al., 2020, p. 14). This can be understood simplistically through three concepts crumbs, capacity, and community (Letouzé, 2012). The crumbs or digital breadcrumbs refer to the actual data generated from multiple sources includes exhaust, web, and sending data (Letouzé, 2015) such as social media interactions, sensor readings, and transaction records. These data crumbs are collected and stored which can be used for analysis. Capacity describes the ecosystem's ability to process data through various tools, processes, methods, software, and hardware (Letouzé, 2015). The big data community represents the collaborative efforts of scientists, engineers, and analysts who work together to extract meaningful insights from the data. The community includes social scientists who are needed to generate solutions and applications for creating meaning out of the crumbs (Letouzé, 2015). This community is essential for driving innovation and making data-driven decisions.

Figure 1

Big Data Ecosystem Adapted Letouzé (2015)



Big Data Community & Data Literacy

When considering who is included in a big data community to solve complex problems related to the SDGs, it is important to consider who needs to be included on the project team (United Nations Development Programme [UNDP] & UN Global Pulse, 2016). UNDP & UN Global Pulse (2016) suggests at a minimum a team should include a project manager, problem solver or domain expert, data holders, data experts, and data privacy and legal experts—all with different required levels of data and domain literacy (see Figure 2).

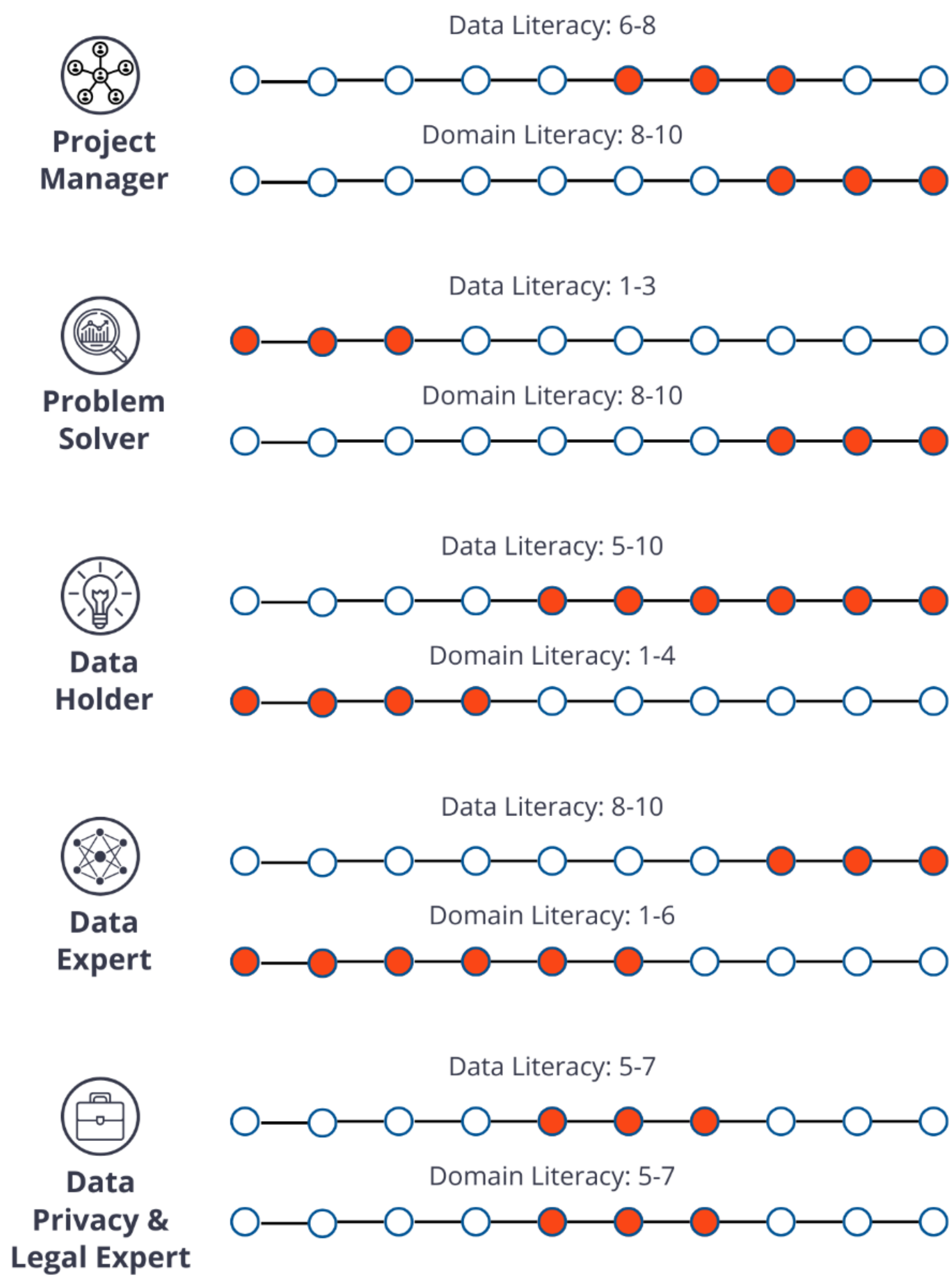
Data literacy is "the ability to transform information into actionable instructional knowledge and practices by collecting, analyzing, and interpreting all types of data" (Gummer & Mandinach, 2015, p. 2). Domain literacy refers to the skills and knowledge related to a particular field or area of expertise. While levels of suggested domain and data literacy vary for each team member, some form of each is needed by each team member.

The project manager is responsible for the organization of the project and keeping all team members on task. For a big data project, this role requires an above average level of data literacy (6-8 on a scale of 1-10) and a high level of domain literacy (8-10). This role requires the highest combined levels of data and domain literacy because they need to understand all facets of the project to work with all team members and stakeholders (UNDP & UN Global Pulse, 2016). The problem solver or domain expert ensures the design of the project meets the application of the domain and needs a high level of domain literacy (8-10) but only a low level of data literacy (1-3).

The data holders are those that have access to or own the data including businesses, organizations, governments, NGOs, etc. (UNDP & UN Global Pulse, 2016). At times, data may be open access and not require a data holder, but when needed these individuals need average to high levels of data literacy (5-10) and lower levels of domain literacy (1-4). Data experts are data scientists, engineers, or visualization specialists that assist with the technical components of analyzing and processing the data (UNDP & UN Global Pulse, 2016). These individuals do not need a strong knowledge of the domain (1-6) but will require the highest levels of data literacy (8-10). The final member of the team is the data privacy and legal expert who oversees the risk mitigation plan (UNDP & UN Global Pulse, 2016). This individual should have an average to above average level of both data and domain literacy (5-7). While varying levels of domain and data literacy are required from different team members, team members should have some form of both to collaborate effectively.

Figure 2

Data and Domain Literacy Needs of Big Data Team Members on a Scale of 1-10



Note. Adapted from UNDP & UN Global Pulse (2016)

These team member recommendations highlight the importance of increasing data literacy in all fields, including those of social scientists in ANR, to best collaborate on big data projects. Data literacy allows all members of a team to contribute to the problem-solving and decision-making processes by understanding what types of data are available and opportunities for harnessing that data. Data literacy has even been conceptualized as the key to using data to progress toward the SDGs (Kabatangare, 2021). This includes increasing the data literacy of domain experts and general citizens, so they can make informed decisions related to their digital usage and how to navigate their production and privacy of data in a datafied world (Sander, 2020). Therefore, while social scientists in ANR begin to explore their role in the big data revolution and AI production, it is essential for us to consider means to increase overall data literacy.

Opportunities & Challenges of Big Data for Development & ANR Social Scientists

The UN Global Pulse (2013) proposed big data as an opportunity to make informed decisions regarding policy, program, and initiative development. Big data can be used for economic development, increasing awareness, understanding, and projections, generating sustainable responses to issues related to agriculture, climate, and the environment, and forecasting policy and change responses (Maaroof, 2015). However, to harness these opportunities, several key recommendations should be considered (Independent Expert Advisory Group on a Data Revolution for Sustainable Development, 2014). These include creating a global consensus on principles and standards, sharing technology and data for the social good, investing in resource capacity development, accessing and mining data, including the right stakeholders, and making good use of big data for action (TRENDS, 2021; UN Global Pulse, 2013). Additionally, big data presents an opportunity to use real time information with better evidence and analytics, which can include a citizen-focused approach (Independent Expert Advisory Group on a Data Revolution for Sustainable Development, 2014). Many of these recommendations require social scientists with specific domain literacy, such as ANR contexts, who can effectively interpret and apply big data insights to address grand challenges. These experts are imperative for translating data into actionable strategies that promote sustainable practices, enhance resources, and improve policy outcomes. By enhancing collaboration between data scientists and domain experts, we can ensure that big data initiatives are both impactful and aligned with the unique needs of the ANR sector.

While there are ample opportunities for using big data for development, there are several challenges that must be considered. While this is not an exhaustive list, a few key pieces are privacy, the digital divide, access, and analytical challenges (UN Global Pulse, 2013). Privacy is “the right of individuals to control what information related to them may be disclosed" (UN Global Pulse, 2013, p. 6). The production of data often raises concerns from individuals about the amount and types of data that are generated daily (UN Global Pulse, 2013). Legal protections, consent, and removal of identifying information are important steps toward ensuring human rights are protected in the digital world (UN Global Pulse, 2013). Access is an additional issue, considering the private sector and large-scale companies own much of the data that could be beneficial to advancing progress toward the SDGs and creating solutions to ANR industry issues. Data philanthropy is a newer concept that creates opportunity for the private sector to help the public sector in their work toward achieving SDGs (UN Global Pulse, 2013) and improving the ANR industry and global food security. In ANR contexts, social scientists play an important role in the development and adherence to ethical standards related to the use of data for the social good.

Particularly when working in international or global contexts, it is important to consider the digital divide and how fragmented data may impact the veracity and validity of available data. Access to mobile devices and the Internet as well as advanced data analyzes technology leads to a divide in the availability and speed of data generation from country to country (UN Pulse, 2013). In ANR, social scientists can play a role in determining groups missing from the data or where culture impacts data generation to assist in collecting additional data and recognizing potential biases in the data.

Analytical challenges including sentiment analysis, text mining, falsification, perceptions versus facts, sampling selection bias, apophenia, and correlation does not mean causation have been identified by the UN Global Pulse (2013) as obstacles for using big data for the SDGs and social good. While sentiment analysis software exists to make meaning out of emotions and opinions, methodologically, it still faces challenges related to accuracy (Wankhade et al., 2022). Similarly, text mining—extracting keywords or events from data—faces similar challenges related to the same words having different meanings (Hassani et al., 2020). Additionally, assumptions are made that those who have access to mobile or digital services are representative of the wider population, which can lead to sampling selection bias (UN Global Pulse, 2013). These challenges present opportunities for social scientists to collaborate in the data analysis process and the creation of technology that produces results more closely aligned with qualitative analysis results.

Other methodological concerns relate to the reliability and validity of the data. Falsification poses a threat when data is fabricated or false with the intention of providing misleading information (UN Global Pulse, 2013). Perceptions and facts are not always the same, which can lead to incorrect conclusions when individuals provide information online that is their perception rather than reality. Additionally, apophenia can occur when patterns and correlations are perceived but do not actually exist (McQuillan, 2016). Similarly, while algorithms may identify patterns, it is important to consider that correlations do not always lead to causation and there may not be a link. Regarding perceptions and human behavior, social scientists play an important role in determining if the findings from big data are a product of one of these methodological challenges or if they provide insight for the agricultural industry. This can be done through theory application, connections to previous research, additional sampling of a set population, or through qualitative methods to validate big data findings. Overall, we must consider that most of the SDGs are focused on humans and how human behavior impacts the wider ecosystem and global landscape, which requires collaborative relationships that include social scientists to assist in the development of analyses and interpretation of data.

Big Data Applications in Agricultural Extension

There are vast opportunities for leveraging big data across agricultural Extension, education, communications, and leadership. The most common and well-known application of big data within the Extension has concerned the use of precision farming, information communication technologies (ICT), and other IoT smart equipment and products (Cropin, n.d.; Kosior, 2017). In the field, products like robots, remote-controlled navigation systems, drones, remote sensing, and computer imaging integrate with progressing machine and language learning models and other analytical tools to produce massive amounts of data. These technologies are often used for surveying, monitoring crops and soil, mapping fields, range- and pastureland. Data generated from these products are used in smart agriculture to help farmers make decisions that can create efficiencies and streamline on-farm management, increase crop yields, improve land management, and conserve resources (Raj & Garlapati, 2020). While data from IoT equipment and products is valuable, big data encompasses on and off-farm datasets which enriches the capacity for richer, more complex analytics and farm insights (Xin & Zazueta, 2016).

By including other data sources, farmers can get a more accurate, comprehensive picture of the various factors (i.e. environmental, economic, human, weather) impacting their operation and success (Kosior, 2017). This information can be used to create models and make predictions about crop and soil conditions, weather and rainfall patterns, fertilizer application, and animal health (Javaid et al., 2023). Ultimately, this information helps farmers make real-time decisions that save them time and money (Nukala et al., 2016). Outside of production, big data can also have immense implications for the agri-food system down the supply chain—supporting transportation, distribution, marketing, and retail of agricultural products globally (Nukala et al., 2016).

Extension and science/ANR communication professionals play a large role in increasing the awareness of big data in agriculture. Much of this work is centralized in connecting the ANR industry, including farmers, ranchers, and communities, with new technologies and usages for big data that assists in solving complex issues. By facilitating access to and knowledge of big data, these processionals can aid stakeholders in tackling challenges related to optimizing crop yields, improving resource management, and addressing environmental concerns. Opportunities exist for Extension communicators to use publicly available big data, like Google Trends, to make informed decisions related to online search behavior and agricultural and natural resources topic areas (Yang et al., 2024). Optimization of word choice and understanding of relationships between online searches can lead to improved communication campaigns and ultimately behavior change. Increasing data literacy for farmers, communities, youth, county leadership, and other constituents is imperative for harnessing the potential of big data, AI, ML, and IoT. Agricultural educators play a vital role in the creation of curriculum, experiential learning opportunities, and professional development. Additionally, agricultural educators can advance curriculum at the high school level to include basic big data literacy components both in- and outside of ANR to increase the overall data literacy of citizens and the future workforce.

Additionally, Extension plays a role in identifying resources and creating partnerships for data philanthropy which can aid in the decision-making process for farmers and communities. This requires academic-industry partnerships embedded within communities and creating networks of experts for big data applications and assisting in creating teams for data related projects. These networks and teams would include faculty, practitioners, and farmers for input. However, this role requires advancement of their own data literacy to ensure they are prepared to collaborate with ANR scientists and data holders for meaningful partnerships.

Extension faculty are known for their knowledge on change and adoption of innovations processes. Big data and subsequent technologies (i.e. AI, ML, and IoT) are innovations that are embedded in a social system (Kshetri, 2014). According to Rogers (2003), the social system includes interrelated individuals who are working towards solution generation for shared goals. Therefore, Extension faculty can and should assist in the development and diffusion processes of new innovations and analyses related to big data to ensure the characteristics of the technology—relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003)—are present and communicated. Additionally, these individuals can work to identify issues related to the digital divide, access, and analytical challenges to ensure solutions are viable for the wider ANR industry and contribute to the SDs.

Many say the future of farming, digital agriculture, and a revolutionized food system is here now. But as the global population continues to rise and agricultural land (Zulauf et al., 2024) and farming operations decline (Mehrabi, 2023), ANR leaders and those with decision-making power across the industry must be poised to respond to dynamic technological advancements, regulatory changes, and evolving challenges. The strength of big data for agricultural leaders is that it creates opportunities for data-driven decision-making, strategic planning, optimizing resources, and supply-chain efficiencies across sectors of agriculture, informing policy creation, encouraging stakeholder collaboration through shared data platforms, and monitoring and evaluating the success of local, national, and global agricultural initiatives.

ANR social scientists can play a pivotal role in policy development related to big data by communicating with policymakers, stakeholders, and communities about the importance of ethical data practices and procedures. They can conduct and disseminate research that includes the vast capabilities of big data for ANR innovations while also considering ethical standards. ANR social scientists should work to ensure the views of individuals involved in the production and future usage of big data—such as farmers, rural communities, and those missing based on the digital divide—are included in policy decisions. Additionally, they can collaborate to develop guidelines and best practices for ethical data collection, storage, and usage, which adheres to privacy standards and consent.

ANR social scientists can leverage big data for informed decision-making in policy, program, and initiative development (UN Global Pulse, 2013). Big data provides opportunities for economic development, creating projections, and generating sustainable solutions to complex problems in ANR such as agricultural, climate, and environmental issues. To take advantage of the opportunities related to big data use, several recommendations must be considered, including creating universal principles and standards, sharing data and technology for social good, investing in resource development, increasing access to data, including the appropriate stakeholders, and using big data to advance the ANR industry and progress towards the SDGs. The domain literacy of ANR social scientists is crucial for interpreting and applying big data projections to address complex problems related to ANR while considering the social system the problem is embedded within. They can play a critical role in translating data output into actionable responses specifically designed for the intended audience. By fostering collaboration between data scientists and domain experts, social scientists can ensure that big data projects and outcomes are impactful and aligned with the unique needs of the ANR sector. This collaboration is vital for making informed decisions that drive progress and sustainability in agriculture.

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