

eVALUation Matters

A Quarterly Knowledge Publication on Development Evaluation



Preparing Evaluation of the Future: Big Data, Modern Technologies, and Shifts in Global Development Priorities

Second Quarter 2020

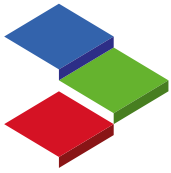


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*From **knowledge** to **action**...*

*From **action** to **impact***

eVALUation Matters

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Second Quarter 2020

Rapid advances in technologies resulting from the fourth industrial revolution (4IR) and related digitization are changing the way information and knowledge are created, used and shared. How have these shifts affected evaluation? How should evaluators adapt to the proliferation of big data or blockchain encryption to avoid becoming obsolete? What do we need to harness and how?

Simultaneously, there have been shifts in global development priorities, such as the move from the MDGs to the SDGs. Are the new tools and technologies available to us conducive to responding to these changing demands? How can they help evaluators to address new challenges?

The ongoing COVID-19 pandemic has brought to the fore many of the above-mentioned issues flagged earlier by proponents of the 4IR, who noted that the 4IR, digitization and disruptive technologies would transform how work and development were approached.

This edition of eVALUation Matters explores how the fourth industrial revolution, digitization and the associated boom in disruptive technologies are shaping the practice of evaluation primarily in Africa, and its implications for the African Development Bank's work.



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“The 4IR provides vast opportunities for incorporating M&E into African and global development policies as well as program evaluation approaches. If appropriately done, M&E has a high likelihood of growing and adapting to a changing environment while addressing worldwide public demands.”

Bernard Okpe, Nigeria Country Department, African Development Bank.

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successes and
failures in evaluation

eVALUation Matters Editorial Calendar 2020:

The editorial calendar for 2020 has been published. Please find the calendar plus guidelines for contributions here: <http://idev.afdb.org/en/document/editorial-calendar-2020>



Find eVALUation Matters at <https://idev.afdb.org/en/page/evaluation-matters-magazine>



From the Evaluator General's Desk

The fourth industrial revolution (4IR), digitization and the rise in disruptive technologies are individually and collectively transforming the possibilities for evaluators to collect, analyze, use and present data on a wide range of variables, including contextual ones, and to explore relationships between them in novel ways. The evolving landscape has led to calls for improvements to the intellectual capabilities of evaluation scholars and practitioners to utilize the available opportunities presented in the technological innovations to develop practical, suitable and sustainable solutions to monitoring and evaluation (M&E) issues. The definition and popularization of the term “disruptive technologies” by the late Harvard professor, Clayton Christensen, has contributed to our understanding of not only how technological innovations impact firms and industries, but also how they impact consumer behaviors, markets, socio-economic systems and more. These technologies also are shaping how we measure the performance of initiatives. Indeed, rapid advances in artificial intelligence, machine learning, human-machine interfaces, and synthetic biology are increasingly demonstrating that technological advances have social, cultural, political, and economic impacts. Technology today has become part and parcel of our everyday fabric—a human issue that demands comprehensive, human-centered approaches.



► *Technology, however, presents challenges as much as it does possibilities and opportunities. To this end, 4IR and the associated rise in digitization and disruptive innovations are like a double-edged sword – with immense opportunities and challenges. The opportunities relate to the possibility of gains in efficiency and productivity that will introduce novel ways of doing things, create new employment opportunities and drive economic growth. At the same time, these technologies pose challenges that are related to issues of privacy, and the possibility of greater inequality, particularly in its potential to disrupt labor markets – with new technology displacing old ways of doing, and employees who are unable or unwilling to retool their skills being made redundant – a point well-articulated by Bamberger and York, and echoed by other contributors to this edition.*

For the discipline of monitoring and evaluation, 4IR and associated disruptive technologies are expected to revolutionize how data is gathered, managed, interpreted and utilized. As Teddy Nalubega & Dominique Emmanuel Uwizeyimana remind us in their 2019 publication ‘Public Sector Monitoring and Evaluation in the Fourth Industrial Revolution: Implications for Africa’, these emerging technological innovations have the capacity to capture and analyze multi-dimensional information from multiple contextual variables, with minimal costs and time required, in both qualitative and quantitative formats. The pace at which technology is transforming our lives is exponential. Regulators, businesses and individuals alike must adapt, or risk becoming irrelevant. Negotiating the evolving evaluation landscape brought about by the emergence of new technologies, together with the challenges they herald, call for capacity development in tandem with an ability of the key evaluation actors – governments, VOPEs, associations and networks, development partners, training institutions – to sustainably harness existing internal synergies and exploit the opportunities presented by the evolving technology landscape.

Against the backdrop of technology’s consequences, still very much a point of debate, this edition of eVALUation Matters, guided by the theme “Preparing Evaluation of the Future: Big Data, Modern Technologies, and Shifts in Global Development ►►

► *Priorities*”, explores the interplay of disruptive innovation and technologies on the discipline and practice of evaluation primarily in Africa, and its implications for the AfDB’s work. Contributors to this edition, drawing on their nuanced understanding of the continent, and the literature on 4IR and evaluation, have attempted to tease-out how the boom in disruptive technologies is changing the evaluation landscape. Individually and collectively, contributors highlight the challenges, opportunities and possibilities that these technologies offer, and how developments will compel evaluators to rethink how evaluations are designed and managed and how findings are utilized. The views expressed by contributors mirror the Bank’s optimism in the potential of 4IR, related disruptive technologies and the digital economy as articulated in two recent publications: *African Economic Outlook 2020 – Developing Africa’s Workforce of the Future*; and, the *2019 Study Report – Unlocking the Potential of the Fourth Industrial Revolution in Africa*.

From my vantage point as Evaluator General, I also see the potential of emerging technologies in revolutionizing M&E globally and in Africa. This will only be accelerated by the consequences of COVID-19, which has already driven evaluators to explore new ways of gathering the data they need to conduct high quality, robust evaluations. For instance, restrictions arising from the COVID-19 pandemic will fast-track the need for evaluators to embrace innovative technologies if we are to stay relevant. Limited mobility will mean remote interviewing (via phone, teleconferencing), use of big data, satellite imagery and geographic information systems to circumvent the inability to get onto the ground, and the employment of artificial intelligence and machine learning to delimit the evaluand (subject of evaluation), amongst others. At the same time, we will need to examine carefully how and to what extent the new technologies can compensate for fundamental deficiencies in the quality of basic data, which is a challenge throughout the developing world. Also, the benefits of such new approaches will only be realized if we use them to better capture effects on the poor and vulnerable and avoid the risk of potentially excluding them because they are “less connected”. ►►

► *I recognize the need for decision and policy makers in Africa, together with evaluators and the wider development community, to pay special attention to 4IR developments, particularly, the effects of these technological innovations on future employment, education, capacity development, and policy. Doing so meaningfully will require new skills training and critical discussions among M&E practitioners, data scientists and the developers of technology to significantly enhance the quality, validity and reliability of the data captured by the technologies. More importantly, as contributors to this edition caution, if Africa seeks to leverage the 4IR, then the continent will need to advance its own variety of evaluation in which its disruptive innovations and related tools—be they design, big data, artificial intelligence, geographic information systems, predictive analytics or otherwise—facilitate its global role beyond clichés to yield transformative development.*

I hope the contributions offer invaluable insights and learning on the interplay between disruptive technologies and evaluation, and how this potentially stands to shape the discipline and practice of M&E in Africa—possibly also including how the Bank undertakes its evaluations going forward. They provide new perspectives that not only inform but also empower the current and next generation of evaluators to embrace technology and to try out novel ways of undertaking and appreciating evaluations.

Happy reading!

About the Evaluator General

Roland Michelitsch is the Evaluator General of the African Development Bank (AfDB). Prior to joining the AfDB in 2019, Roland was at the Inter-American Development Bank (IDB), where he led evaluations of private and public sector initiatives. Earlier in his career he worked at the International Finance Corporation (IFC), where he managed the investment unit of the Development Impact Department. He also led IFC's project evaluation system and framework, and evaluations on various topical issues. He holds a PhD and MA in Economics from the University of Arizona, USA, and an MBA from the University of Graz, Austria



Transforming Evaluation in the 4th Industrial Revolution: Exciting Opportunities and New Challenges

Africa, much like the rest of the world, is in the throes of a fourth industrial revolution – one characterized by digitization and disruptive technologies. These developments are impacting many aspects of society including evaluation. While some of these technologies may be unfamiliar to evaluators in Africa, the rapid rate at which the cost of these novel technologies is falling, and becoming accessible, will increase their application, offering tremendous opportunities to strengthen the contribution of evaluation to the development challenges.

Michael Bamberger, Independent Evaluation Consultant and Peter York, BCT Partners.

Key Messages

- The 4IR will compel evaluators to rethink how evaluations are designed and managed as well as how evaluation findings are used.
- Despite the need to adapt to a new and complex data ecosystem, 4IR offers a range of exciting resources and opportunities for evaluators.
- Training of evaluators must be significantly updated to cover the tools and techniques of data science and their application to evaluation.

Introduction: The New World of the 4th Industrial Revolution and the “Disruptive Elements”

It is widely acknowledged that Africa is entering a 4th Industrial Revolution (4IR) which will be driven by digitization and new information technologies. While 4IR offers tremendous opportunities for both the public and private sectors as well as for civil society, it will also be very disruptive, challenging conventional industrial and development paradigms and producing both winners and losers. As we will discuss, new information technologies also offer tremendous opportunities for how programs and policies are evaluated and how evaluation findings are used to improve program design and management. However, these technologies will also be disruptive and, whether they wish to or not, evaluators will be forced to rethink how evaluations are designed and managed and how evaluation findings are used. While many will welcome these changes, others may feel threatened or will resist them because the new ways to collect and analyze data seem to challenge accepted evaluation paradigms and “best practice.”

The new world of 4IR and the implications for evaluation

The technological changes described in the African Development Bank (AfDB) publication *Unlocking the Potential of the Fourth Industrial Revolution in Africa (2019)*, which are discussed in the following section, will have profound implications for how evaluations are designed and evaluated. However, these technologies will be embedded in broader structural changes that will create the new data science ecosystem within which evaluations will be conducted. Some of these broader structural changes, which will profoundly affect the practice of evaluation, include:

- **Closer interconnectedness among different parts of the economic, political and other systems.** This will require that many evaluations must adopt a broader systems analysis focus to model and track these interactions which also evolve and change over time.
- **Evaluators will need to learn to navigate the new information ecosystem.** The data used by evaluators will be generated, controlled and ➤

- ▶ disseminated in new ways, and there are many new actors involved with regulation, marketing and creation of new apps.
- **The speed of change will be much faster.** This will affect both the speed at which new technologies are developed and at which they spread, and the speed at which programs develop and change.
- **The scale of many programs and interventions will increase.** This growth will in part be driven by the amount and speed of information feedback made available through rapid advances in technology solutions and applications for those on the front lines. This will in turn put pressure on evaluators to be able to do their work in a more efficient and timely manner. These changes will require the integration of real-time data science techniques into the evaluator's methodological toolbox.
- **Any intervention is affected by the broader context within which it operates.** This requires the use of complexity-responsive evaluation designs, and data collection systems that can generate and analyze the kinds of data required to model complexity¹.
- **The concentration of power and the digital divide.** In order to benefit from the new information technologies, program evaluators will need the resources to access or generate large volumes of data and to conduct more sophisticated kinds of data extraction, transformation and analytics. This offers the potential danger of accentuating the digital divide and the gap between organizations and socio-economic groups who do and do not have access to these resources. Another power imbalance concern is the potential use of data collected on and about poor and vulnerable groups

without their knowledge, or without their consent for use. Evaluators will need to tread cautiously as they engage in the use of these kinds of data.

The Disruptive Elements

In addition to these broader structural changes, the AfDB (2019) publication identifies six emerging technologies that will be “disruptive” to economic and social development throughout Africa. The publication does not directly discuss the implications for evaluation, but it is likely that five of these technologies will directly impact the field of evaluation²:

New technologies for data collection

1. **Big data:** Huge increase in the types of data that are feasible to collect, and dramatic reduction in the time and cost of data collection.
2. **Internet of Things (IoT).** Ability to collect objective data on human behaviors, choices, health status, environmental conditions, interactions, etc., for example via smart watches that can monitor a person's location, movement, physiological state, and communications with others, and monitors that track numbers of people using community water supply or toilets. IoT produce and store these data, which could be leveraged for more complex program evaluations.
3. **Drones [and satellites].** Ability to collect, on a continuous basis, aerial images of infrastructure, economic activity, migration patterns, temperature, moisture levels and other characteristics of the natural environment. Low-level high-resolution drone images can be combined with high-level satellite images covering very large geographic areas. ▶

► New technologies for data analysis and prediction

4. **Artificial intelligence [and data mining].** Machine learning algorithms can be trained to find natural experiments in historical big data to derive quasi-experimental conclusions about attribution/contribution of programs and policies to population or community outcomes. Once these algorithms have been trained on one or more datasets, it is possible to automate the evaluation and learning process, significantly reducing the time and resources it would typically take to conduct an evaluation.

New technologies for data security, privacy and ownership

5. **Blockchain.** The biggest concerns regarding the use of big data for any purpose, including evaluation, are the security, privacy and ownership of data, particularly data that are gathered ‘unconsciously’ – i.e., gathered without a person’s explicit understanding of, and agreement with, the use of their virtual transactions for purposes other than the transaction. Blockchain is a solution to this problem. It encrypts all virtual exchanges through a decentralized distributed ledger. When data are centrally held, it is more vulnerable to being hacked. With blockchain, every transaction is recorded in a chain (sequential ledger), and there are many decentralized nodes (computers) that hold a copy of each blockchain. If someone tries to alter a block of information (data), the transaction – which is encrypted – gets checked with all other copies of the chain. If the same block’s (transactional data) copies on other computers don’t match, the data are not exchanged. This allows for very strong data security and privacy. The upside of blockchain is that it

protects data and empowers people to own their data, and always requires them to grant permission to access it.

Why are these technologies considered disruptive for evaluation?

While these new technologies offer great potential benefits for many kinds of evaluation organizations, they will also inevitably cause significant disruptions to the practice of evaluation:

- First, many evaluators are currently not very familiar with the new technologies for data collection and analysis, so there will be a requirement for major capacity development for many evaluators;
- Second, the collection and analysis of the new kinds of data will often require significant investments in equipment, software, staff and consultants;
- Third, there will often be a need to restructure the relationships between evaluation offices, data centers and operations departments;
- Fourth, there is likely to be resistance to some of these changes because veteran evaluators may feel threatened by the new technology, or are resistant to the need for retraining;
- Fifth, there will be a need for reorganization and team building in some evaluation offices as staff and consultants with the new sets of data science skills must be integrated into offices where many current staff do not have these skills; and,
- Finally, on a broader structural level, it may be easier for larger and better resourced organizations to adopt the new technologies, while smaller and less well-resourced organizations may become marginalized ►►



- ▶ from some potential programs and funding sources. For example, funding agencies may prefer to support organizations that are already able to use big data in their management and evaluation systems.

Exciting Opportunities for Evaluation in the Age of 4IR

Despite the need to adapt to a new and complex data ecosystem, 4IR offers a range of exciting resources and opportunities for evaluators to adapt to the rapidly changing environment in which programs operate:

- Access to data is becoming faster and cheaper, and the types of data are increasing rapidly. The new analytical tools for creating integrated databases make it possible to combine multiple kinds of data into a single database. This means that it is now possible to combine, for example, survey data, geospatial data, phone call records, social media posts, ATM transaction records and audio-visual data into a single data platform. Text analytics also makes it possible to analyze the huge volumes of PDF files that most agencies have accumulated over the years³.
- The cost of data collection means that most evaluations try to reduce the sample size to the minimum possible to achieve a required level of statistical power. However, it may now be possible to work with the total population, which permits more granular analysis and more sophisticated analytical models.
- While it is widely acknowledged that most programs are “complex” and that program outcomes are affected by a wide range of contextual variables (economic, political, demographic, environmental), the cost and complexity of collecting data on the key contextual variables has meant that

until now it was usually not possible to incorporate these contextual variables into the evaluation design. It is now possible to incorporate these variables and to start to use “complexity-focused” evaluation methods.

- Systems analysis (a key element of complexity theory) can now also be incorporated into the evaluation.
- Big data can also provide enough cases needed for deeper analyses of positive outliers/positive deviants, to refine our understanding of what works.
- Techniques such as geospatial analysis now make it possible to collect data over long periods of time, including before a project begins and after it ends. This makes it possible to evaluate program sustainability, something that has rarely been done in the past.

Transforming the Nature of Evaluation in the Age of Big Data

This section identifies some of the cutting-edge developments in the field of big data and data science which are already starting to be tested in the field of evaluation. While some of these applications will be unfamiliar to many evaluators working in developing countries, or in less technologically advanced regions of the US and other industrialized nations, the rapid rate at which the costs of these applications are falling, and at which they are becoming accessible to non-specialists, mean that their application will rapidly increase around the globe. Whereas previously most of these applications required the purchase of expensive, proprietary and technically complicated software or contracting expensive consultants, they are rapidly becoming available to a much wider range of organizations, including, for example, national NGOs and resource constrained government agencies. The rate at which the introduction of these ▶

► technologies is likely to take place, will require and produce a much more rapid transformation of evaluation practice than has ever occurred in the past. This section ends with a brief discussion of some of the issues that must be addressed during the transformation.

Cutting-edge evaluation technologies⁴

Big data technology combined with machine learning algorithms will advance the practice of evaluation. Program evaluations using existing data and statistical matching techniques to reduce selection bias-like propensity score matching-have long been used in over 100,000 studies in fields like medicine and economics. With advances in the capture of big data and the application of machine learning algorithms for predictive and prescriptive analytics, the time and cost of conducting evaluations using observational data will be reduced exponentially over the next few short years. Linking program administrative data with survey data, personal use/tracking/social media and publicly available contextual data, the field of evaluation will gain the low-cost capacity to quasi-experimentally measure attributable program outcomes, identify emerging patterns of promising practices and generate formative insights for front line implementers.

Technological advances have led to analytics platforms that combine traditional statistical modelling tools with machine learning to much more rapidly, repeatably and economically conduct evaluations. There are providers in the US that have built rigorous quasi-experimental, mixed methods evaluation workflows that sit on top of their program administrative data. These automated evaluation workflows extract, transform and load these organizations' longitudinal program data into an analytics workflow; conduct all data cleaning and

transformations, including calculating scales and constructs; find all naturally occurring experiments in history with matched comparison groups of cases; conduct inferential analyses to test and accept or reject program hypotheses, including producing effect sizes, dynamic findings tables and visualizations; as well as generate implementer-guided language for recommendations that will improve the odds of success for each individual case/beneficiary. Programs can now probabilistically evaluate every case, in relation to their matched comparison group members, labeling/tagging each individual with one of four outcomes: (a) **attributable success**—got what was needed (group-specific high-probability recommendations) and succeeded; (b) **unknown needs**-got what was needed but didn't succeed; (c) **unattributable success**-didn't get what was needed but succeeded anyway; and (d) **unmet needs**-didn't get what was needed and didn't succeed.

Evaluations that use structured program data will be further enhanced qualitatively through rapidly advancing natural language processing algorithms and the ability to conduct more targeted and precise qualitative inquiry. Government agencies are beginning to use and apply advanced natural language processing algorithms that better understand context by being trained using datasets like all of Wikipedia. For example, these types of natural language processing algorithms have been trained to augment the review of narrative grant proposals and reports such that a human with the support of machine learning algorithms was eight times faster than human-only coders, without any loss of accuracy. There are mental health providers that have developed evaluation algorithms that can code and score psychiatrist notes for use to generate testable evaluation findings. In addition to natural language processing advances, the identification of every case's outcome status (e.g., unmet needs, attributable ►

► success) via evaluation algorithms has resulted in practitioners qualitatively investigating and co-creating meaning from specific cases that were identified by the analytic process. These qualitative ‘learning exchanges’ were timelier, more focused and less costly than qualitative evaluation methods with less targeted sampling plans. Additionally, practitioners often generated new hypotheses and requested better data points/metrics moving forward. As a result of this ownership of the qualitative meaning-making process, they were more motivated to gather new data. The automation of quasi-experimental evaluation using structured observational data science methods will diminish the need for people to spend so much time getting, preparing and manually analyzing the data, freeing them up to deepen their qualitative understanding of a program experience. Qualitative advances will further deepen an understanding of complexity, as well.

The challenges of transformation

The speed with which these innovative evaluation technologies are likely to evolve means that development agencies and the evaluation sector must anticipate and start to plan for these transformations so as not to be unprepared when these innovations start to be introduced. The field of evaluation is sometimes conservative and resistant to change, so a more dynamic change-management approach will be required. A first challenge will be to understand and to navigate the unfamiliar big data ecosystem (discussed in the introduction). Policy-makers must also address the potential risks that larger, better resourced agencies will be able to take advantage of these technologies, whereas smaller or less well-resourced agencies might be left behind. This potential **digital divide** could have wider consequences, as some funding agencies might be attracted to the more technologically advanced agencies,

such that funding might be reduced to less technologically advanced agencies, diverting resources away from experienced but less technologically advanced agencies. The process of transformation may be disruptive as well – established monitoring, data management and evaluation systems may have to be changed – with increasing demand for new staff with data science experience and threats to the job security of many less technologically adept staff. Experience shows that technological change is always more disruptive than claimed by its proponents.

Potential Applications of Big Data in AfDB Evaluations: The Case of the Impact Evaluation of a Road Construction Project in Ghana

This example is used as a hypothetical example to illustrate the range of big data tools and techniques that could potentially be used in AfDB evaluations. It is not intended as a recommendation that these techniques should have been used in this evaluation.

The Ffulso-Sawla road project in Ghana⁵ was selected by IDEV in consultation with the AfDB’s Infrastructure and Urban Development Department as suitable for a rigorous impact evaluation from among a group of new transport projects⁶. The project involves the construction of 147.5 km of road between Ffulso and Sawla with ancillary roads to major settlements, with complementary infrastructure (e.g., boreholes), compensation and resettlement for families that had to be relocated. The purpose of the project is to promote a range of socio-economic benefits which, in addition to improved efficiency of transport, include access to schools, health and other public services.

The purpose of the evaluation is to assess the net effect of the road and ancillary related works on: i) intensity of traffic, travel time and travel cost; and ►

► ii) household income and employment, and access to social and economic services. The evaluation will examine the causal factors affecting impacts and the differential impacts on women and men. The evaluation proposes to use a quasi-experimental design that will statistically match communities and areas affected by the project with similar areas that are not affected⁷.

It is proposed that the evaluation will mobilize 4 data sets: i) a traffic survey, ii) a household survey, iii) a settlement survey, and iv) a tourism survey. Various existing government data sets will be utilized (i.e., Living Standards Surveys and core welfare indicators from the census, GIS data sets covering the whole country, project baseline survey and origin/destination surveys). After an assessment of the adequacy of these data sets, the possibility of generating new data sets may be considered.

Potential sources of big data

The following are some of the potential big data sources that could be considered for this and future transport evaluations.

A. Geospatial analysis generated from satellites and drones. Have proved a cost-effective way to create more rigorous quasi-experimental designs as it is possible to match project and comparison groups on a wide range of socio-economic indicators (e.g., housing quality, community infrastructure and quality of maintenance, soil quality and agricultural output, demographic movements and community growth rates, and estimates of the economic level of the household and community). A great benefit of satellite data is that it is often possible to obtain longitudinal data sets which may cover periods of up to 20 years so that changes can be tracked. A wide range of indicators of economic development

are now available including: using light emissions from communities at night as an indicator of the economic status of communities, heat emissions from factories as an estimate of production, types of roof construction as an indicator of economic level of a community.

- B. Mobile phones.** Provide a cost-effective way to collect and analyze socio-economic survey data which can also include audio-visual material (e.g., photos taken from the same location every year to monitor changes in household and community conditions). They can also be used to collect time-use and travel data from a sample of subjects, information on use of public services and using data on daily and weekly air-time top-ups as an estimate of short-term changes in poverty.
- C. Call-center phone call records.** Can be used to track mobility, and in some cases air-time top-ups.
- D. Social media.** Sites such as Facebook and Twitter generate large amounts of information on users' attitudes and behavior. They provide valuable information on attitudes to programs and services (such as roads, schools, health services) and on use of these services. These sites provide free tools for the analysis of the tweets and posts. They are valuable tools for program evaluation, but it is important address questions of bias as the people who use these sites are never representative of the total population of interest.
- E. Data analytics.** Machine learning algorithms can be trained to more accurately find matched comparison groups by building predictive models for determining each community's 'likelihood' to receive road and ancillary works. This predictive matching process often proves more accurate and valid than ►

► expert-matching alone. Evaluators will input all the contextual, environmental and socio-economic factors that hypothetically predict whether a community would receive the infrastructure support. This predictive matching process will significantly reduce selection bias. The matching variables (inputs) could also include specific local political factors. The resulting matched community segments (based on predictive likelihood to receive roads and ancillary works) best ensure that the evaluation controls for these contextual and situational factors. Then, machine learning algorithms can be trained to find, inferentially evaluate and determine effect sizes for the matched communities that were 'naturally' randomly assigned to roads and ancillary works versus those that were not. All of this can also be automated such that the evaluation can be carried out very cost-effectively and in real-time, as the project moves forward.

Conclusion

The rapid evolution of the tools and techniques of big data and data science offer tremendous opportunities to strengthen the contribution of evaluation to the development challenges of the 4IR in Africa. The increased access to tools to broaden the kinds of data that can

be collected and to the power of data mining, AI and predictive analytics, mean that evaluators will be able to greatly reduce the time and effort spent on data collection and routine analysis, so that they can apply their professional expertise in the design, conduct and interpretation of the meaning and significance of the data and the analysis. However, the process of transformation to the new information ecosystem will be potentially disruptive. So, evaluators and data scientists must focus on several priority tasks.

First, the professional training of evaluators must be significantly updated to cover the tools and techniques of data science and their application to evaluation. Similarly, data scientists must become familiar with the principles and approaches of evaluation practice. Second, evaluation offices must be reorganized to strengthen their linkages with data centers and with other colleagues working in big data within their own organizations. Third, finance departments within governments and international funding agencies must explore ways to support the necessary infrastructure for development agencies and their evaluation offices to fully utilize the new technologies. Finally, the development community must actively seek opportunities for evaluators and data scientists to cooperate, and to critically assess the value-added of the integration of evaluation and data science in the field.

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Endnotes

1. See Bamberger et al. (2016) *Dealing with Complexity in Development Evaluation*. The authors propose that the interactions among four dimensions of complexity must be addressed in most evaluations: 1) complexity in the program being evaluated, 2) complex interactions among the different agencies and stakeholders involved in the program, 3) the multiple economic, political, administrative, socio-cultural and environmental factors that influence the program, and 4) the non-linear patterns of causality.
2. The only disruptive element that will probably not affect evaluation is 3D printing.
3. For example, it is possible to use machine learning to identify and categorize all references to gender or human rights in an organization's data files.
4. For a more detailed discussion of these new technologies, see York, Bamberger and Olazabal (2020) *Measuring results and impact in the age of big data: The nexus of evaluation, analytics and digital technology*. New York: Rockefeller Foundation.
5. IDEV (2019) *Impact evaluation of the AfDB-Funded Ghana Fufulso-Sawla Road Project: Approach Paper*.
6. See IDEV (2019) p.5 for the reasons for selecting this project for the impact evaluation.
7. For a discussion of the approach for identifying the counterfactual see IDEV (2019) Section 4.3

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Authors' profile

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Using Machine Learning for Climate Related Impact Evaluations

The article highlights the use of machine learning and artificial intelligence in climate change impact studies in Malawi and Mali. Both techniques deliver new ways to evaluate program impact and enable flexible and customizable processes that can accommodate important differences in region, sector, and data availability. The techniques can transform an impact evaluation by measuring more without overburdening program participants, providing a more holistic picture of the baseline and endline context, and generating impact measurements that include environmental and human information in one measurement.

Ben Leo, Shaan Pattni, Catherine Winn, Quinn Lewis, Christina Paton & Melissa Persaud, Fraym¹.

Key Messages

- Recent technological advances, notably machine learning and artificial intelligence, have the potential to affect all impact evaluations.
- Machine learning and artificial intelligence enable the creation of a complex, detailed portrait of climate vulnerability, which is comprehensive, data-driven, and human-centric.
- Machine learning quickly and continuously monitor program areas, identify specific components of adaptive capacity, and evaluate how program activity help to address such gaps.

Introduction

According to the Brookings Institute, seven out of the ten countries considered most threatened by climate change are in Africa. In addition to immediate environmental consequences such as increased or irregular flooding, drought, and natural disasters, climate change is also exacerbating long-standing development challenges like water access, food security, stagnant malaria rates, and conflict. The African Development Bank (AfDB) predicts that climate change adaptation costs will reach three percent of annual GDP for African countries by 2030 (Bishop 2017: 88-89). Responding to these compounded challenges requires a revolutionary approach with an impact evaluation strategy to match. Integrating climate change analysis into traditional approaches to development entails a new understanding of the threat that is inseparable from traditional issues such as poverty and food security. As programs expand to include climate risk mitigation and increase community resilience, impact evaluations must adapt to reflect a new understanding of the threat of climate

change: one that is interwoven with people and their livelihoods (Brooks et al. 2018).

In this article, Fraym examines the potential for applying artificial intelligence (AI) and machine learning (ML) to impact evaluations. We begin by exploring several AI/ML-based approaches that will become increasingly relevant for efficiently assessing African communities' vulnerability to climate change. Next, we outline a modified vulnerability index that builds upon past studies, which we then map down to the 1 km² level. Third, we apply this new approach to Malawi and Mali to highlight how this type of localized vulnerability mapping can provide actionable insights for program design and ongoing monitoring efforts. Lastly, we conclude with several takeaways and areas for further exploration.

Using AI/ML for Impact Evaluations

Traditional data analysis in impact evaluations was limited to aggregated or national level data or broad, time-consuming baseline and ►►

► end-line data collection efforts. Recent technological advances now enable analysts to incorporate hundreds of indicators into their understanding of impact and vulnerability. For those examining the human consequences of climate change, this insight is invaluable. Again, countries which are disproportionately affected by climate change are often the world's most data-poor as well. ML algorithms can expand the reach and applicability of existing data sets to provide community insights where local-level data is difficult to access, or altogether nonexistent.

AI/ML technology and the data produced have already contributed to multiple components of traditional impact evaluations around the world. AI/ML have the potential to affect every core impact evaluation concept, from measuring outcomes to targeting treatment groups (McKenzie 2018). In Sri Lanka, researchers used high spatial resolution satellite imagery to estimate poverty and economic well-being (Engstrom et al. 2017). In rural India, AI/ML allowed World Bank economists to derive data on outcomes traditionally difficult to measure from village assembly transcripts (Parthasarathy et al. 2019). Research on food security demonstrated AI/ML technology's ability to target treatment groups for outcomes in their forecasts of food security in the Middle East and North Africa (Moody et al. 2017). In Colombia, researchers overcame ambiguity and bias-prone estimation of causal effects using machine learning to analyze data on ex-combatant recidivism (Samii et al. 2016). These innovations are part of a growing library of published work using AI/ML technology to revolutionize impact evaluations. In the case of targeting, monitoring, and evaluating efforts to mitigate climate change, these types of algorithms can be especially powerful.

Fraym is at the forefront of applying machine learning to data in developing countries,

especially those experiencing the effects of climate change. Fraym uses advanced ML algorithms to combine satellite imagery and microdata from household surveys to provide comprehensive insights into people, their communities, and their livelihoods at the local level. Using publicly available data, we create predicted layers at the one square kilometer resolution level for indicators like poverty, asset ownership, employment, and other socioeconomic and demographic indicators. These high-resolution datasets can then be incorporated into deeper analysis conducted by researchers, analysts, and evaluators. Over the past year, Fraym analysts have been leveraging our data to build comprehensive indices of vulnerability to the world's most pressing threats.

For our assessment of climate change, we utilized a suite of predicted data layers to analyze vulnerability across dimensions that account for human-centric complexities. Outside of Fraym data layers, data was sourced from organizations such as the United States Geological Survey and the National Oceanic and Atmospheric Administration. As development efforts shift to incorporate climate change mitigation and vice-versa, impact evaluations must do the same. Our machine learning methodology is uniquely situated to reflect this shift. Previous efforts to map climate change vulnerability focused exclusively on environmental data like incidences of flooding, droughts, or natural disasters—indicators that restrict our understanding of climate change to environmental issues alone, leaving out a critical understanding of the adaptation potential and resilience of the people and communities living with this threat. Utilizing our hyper-local data on human populations and community attributes, we saw an opportunity for improvement.

Specifically, AI/ML technology allowed Fraym analysts to include over twenty indicators on both environmental aspects and human-centric factors that reflected communities and ►►

► their resilience—like access to bank accounts and food insecurity, as well as proximity to infrastructure. The result is a complex, detailed portrait of vulnerability to climate change that enhances our understanding of previously less accessible contextual indicators—resulting in a more comprehensive, data-driven, and human-centric view of climate vulnerability. This type of detailed, hyperlocal analysis has the potential to radically transform impact evaluations in areas where data and its applications have been previously severely limited, to be targeted, comprehensive, and insightful.

Methodology

Fraym's conception of vulnerability to climate change expands upon a strong foundational body of research and scholarship from organizations like the International Food Policy Research Institute (IFPRI), the United States Agency for International Development (USAID), and the AfDB. Consensus on climate change, vulnerability, and resilience is growing among these and other institutions who have set a standard of incorporating socio-economic indicators into definitions of climate vulnerability. Our AI/ML technology and methodology enable this valuable set of work to continue to expand in breadth, detail, and functionality for impact evaluations.

Many, including Fraym, follow the United Nations' Intergovernmental Panel on Climate Change (IPCC) threefold outline of contributing factors: exposure, sensitivity, and adaptive capacity (Hahn et al. 2009). Choice of indicators differs within each of these buckets depending on regional contexts and availability of data (Table 1), although many factors remain consistent for potential comparisons across the continent. The first component—exposure—captures the strength and frequency of extreme climatic weather, such as drought or flooding. We drew from geospatial data

and satellite imagery to pair environmental conditions on the ground with household-level data on susceptibility to shocks as determined by reporting of droughts, irregular rainfall, and floods. The second component—sensitivity—measures the factors that could spark or worsen the impact of a climate shock in an area, such as agricultural methods, types of farmers, and access to public services. Fraym defines sensitivity with measures of food and water security, agricultural practices, and household composition. These indicators draw from microdata on community characteristics like dependency ratios, access to improved water sources, and the proportion of households engaged in agriculture. For the final adaptive capacity component, we compiled over fifteen indicators to measure four major categories of capital: social, human, financial, and physical. These groupings include education completion rates, access to agricultural markets and finance, income levels, extension services, and other indicators. In order to combine the indicators across the three components of exposure, sensitivity, and adaptive capacity, and construct the climate vulnerability index, we conducted a principal component analysis in line with previous approaches taken by IFPRI and African and Latin American Resilience to Climate Change (ARCC).

The resulting map of climate change vulnerability provides a more comprehensive picture of the most affected communities and their potential for recovery and resilience. Our machine learning-produced data, combined with learnings from previous climate vulnerability indices, can deliver a new way to evaluate program impact. This new approach paves the way for a flexible and customizable process that can accommodate important differences in region, sector, and data availability. For implementers aiming to tailor their evaluations in areas sensitive to climate change, localized insights into vulnerability and the driving factors that differ for ►

Table 1: Climate Vulnerability Index Methodology²

Component	Type of indicator ¹	Indicator used in vulnerability index
Exposure	Hazard events	<ul style="list-style-type: none"> ■ Percent of community reporting a drought in the last year ■ Percent of community reporting irregular rainfall in the last year ■ Percent of community reporting a flood in the last year
	Change in environmental or climate conditions	<ul style="list-style-type: none"> ■ Change in average monthly rainfall between 1960-1990 and 2000-2017
Sensitivity	Agricultural practices	<ul style="list-style-type: none"> ■ Percent of agricultural households with 2 hectares or less of cultivated land (smallholders) ■ Average crop diversification index (1 divided by the number of crops) ■ Presence of irrigation scheme in community
	Community structure	<ul style="list-style-type: none"> ■ Dependency ratio
	Food and water security	<ul style="list-style-type: none"> ■ Percent of households that were food insecure in the last 12 months ■ Percent of households relying on unimproved water source
Adaptive Capacity	Social capital	<ul style="list-style-type: none"> ■ Presence of a farm support organization in the community ■ Percent of agricultural households using extension services
	Human capital	<ul style="list-style-type: none"> ■ Literacy rate for people aged 15 and older ■ Percent of household heads with at least primary education ■ Percent of female-headed households ■ Average age of household head
	Financial capital	<ul style="list-style-type: none"> ■ Percent of households that have taken out a loan in the last year for business or farming ■ Average amount borrowed in the last year for business or farming purposes ■ Average net cash farm income ■ Average total farm size
	Physical capital	<ul style="list-style-type: none"> ■ Percent of households with access to piped water ■ Average distance to nearest road ■ Average time to school ■ Average distance to nearest agricultural market ■ Percent of households with electricity ■ Distance to health clinic ■ Percent of households with a mobile phone

► each community have the potential to guide monitoring efforts from the outset of a project. For example, within the adaptive capacity indicators, we can measure forms of information access, such as literacy levels and educational attainment, or access to financial capital like obtaining loans, both of which contribute to a household’s ability to respond to adversity. Data collection throughout the project can then focus on the key indicators that the index draws out for individual communities, mitigating inefficiencies and unnecessary data collection efforts. Segmenting especially vulnerable areas or sectors also can inform a project design that targets highly specific opportunities to improve adaptive capacity

at the household level. Bringing our new approach to this growing body of research enables climate vulnerability indices that are comprehensive and practical for impact evaluations, project monitoring, and for informing policy decisions.

Case Studies and Analysis – Malawi and Mali

In the following section, we explore the application of AI/ML in evaluation of existing development projects in Malawi and Mali to demonstrate what is possible without launching a full-scale baseline survey. In both cases, we leveraged Fraym data to ►►

► analyze the livelihoods of people living in project areas highly vulnerable to climate change. For each country, our analysts created a climate vulnerability index map at the one-square kilometer resolution level to investigate factors that drive differences in vulnerability.

Malawi

The vulnerability map of Malawi highlights the country’s southern region as most vulnerable. In 2017, 46 percent of households in southern communities experienced some form of drought, 10 percentage points higher than households in the central region, and 25 percentage points higher than the north. As a practical application of our hyper-local capabilities, we chose the Mangochi district, where USAID’s Office of Food for Peace launched a US\$75 million development food security

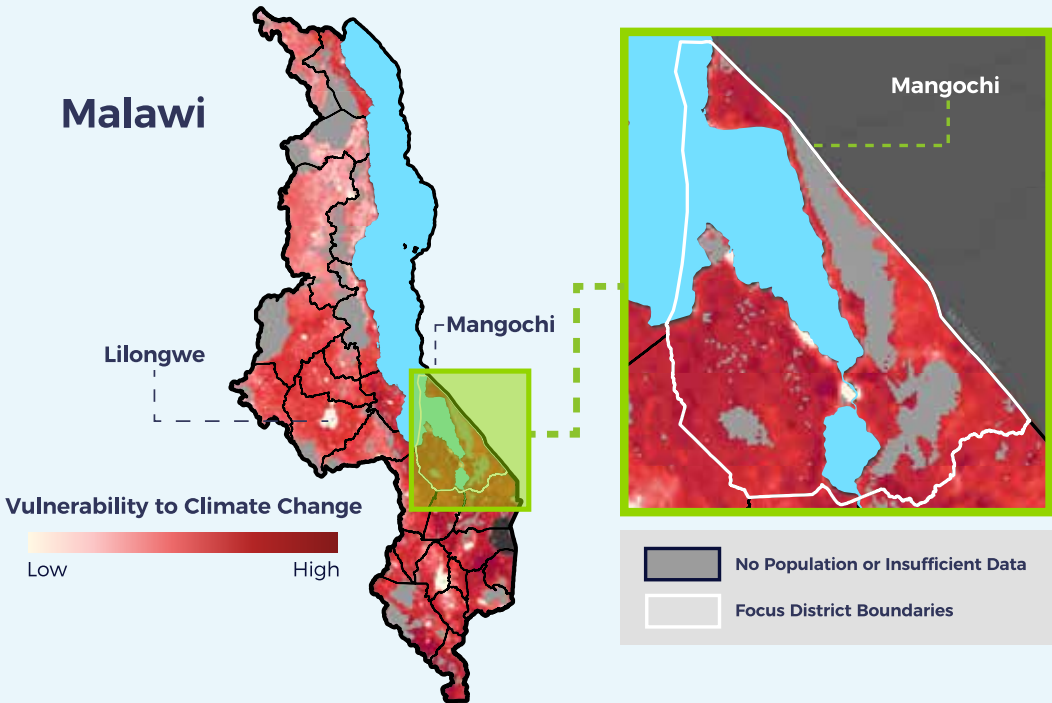
activity in 2019 (USAID 2019, USAID 2020a). This district has approximately 1.1 million people, or six percent of the total population of Malawi.

Profile

We leveraged our database of adaptive capacity indicators and its 2017 climate vulnerability index map for Malawi to quantify levels of adaptive capacity for the most climate vulnerable areas of Mangochi district (Figure 1). According to Fraym’s climate vulnerability index, Mangochi ranks as Malawi’s fifth most climate vulnerable district. Among the three index components (exposure, sensitivity, and adaptive capacity), Mangochi district has the second lowest adaptive capacity out of the 28 districts in the country, meaning its resilience against climate-related shocks is relatively weak compared to other districts. That said, vulnerability to climate change is not uniform across the district. ►

Figure 1: Climate Vulnerability Index Map – Malawi

Climate Change Vulnerability in Malawi



▶ Again, using the climate vulnerability index, we segmented households between lower and higher areas of vulnerability and quantified their adaptive capacity. In doing so, we defined areas that are highly vulnerable to climate change in Mangochi as those higher than the average climate vulnerability index value of Malawi and analyzed indicators related to the adaptive capacity in the form of human, financial, and physical capital as follows:

- **Financial Capital:** Mangochi district has the lowest proportion of households that took out a loan or have access to a bank account. On average, 11 percent of households were able to obtain a loan for their business or farming enterprise in highly vulnerable communities of the district, compared to 20 percent of households in less climate vulnerable communities. A similar pattern holds for access to bank accounts, where 11 percent of households had access compared to 19 percent in less vulnerable areas of Mangochi. Overall, access to credit is lower based on these two indicators in the highly vulnerable climate communities of the district.
- **Physical Capital:** According to IFPRI, the quality of physical capital, or infrastructure, can improve the adaptive capacity of communities vulnerable to climate change. The presence of more infrastructure inherently reduces physical isolation of more remote communities, which presumably can improve disaster response and promote commerce. An analysis of physical capital indicators from our data shows that households in highly vulnerable communities are 14 kilometers away from roads on average, compared to 7.5 kilometers away in less vulnerable communities. Furthermore, less than 2 percent of households in high-vulnerability areas have piped-in drinking water compared to 35 percent of households in less vulnerable communities of the district. Similarly,

a review of asset ownership like mobile phones shows that household access in highly vulnerable areas is half that of less vulnerable areas (36 percent versus 79 percent).

- **Human Capital:** Literacy levels are a useful proxy for understanding information accessibility and allow us to quantify the disadvantages that women face in the context of climate vulnerability. Fraym data shows that Mangochi district has the lowest levels of completed primary education for female heads of household in Malawi and the third-lowest literacy levels for women above 15 years old. Among female heads of household within the district, only 18 percent have completed primary school compared to 60 percent who have completed primary school in less climate vulnerable communities.

Combining the climate vulnerability index with our adaptive capacity indicators allows us to have a comprehensive baseline understanding of both community-specific climate vulnerability but also the current levels of adaptive capacity at the household level. As the Food for Peace program continues, we can measure the change across these indicators as well as include the vulnerability dimension in the contextual analysis of the evaluation of the overall program.

Mali

Nearly two thirds of Malians, or approximately 14.4 million people, are highly vulnerable to climate change. This high figure stems from a concerning combination of factors, including low and variable rainfall levels, high rates of small-scale agriculture, and lack of access to essential services like finance, education, and clean water. Nationwide, Malians are ill-equipped to handle the negative effects of climate change given these environmental and socio-economic factors. ▶

► Vulnerability to climate change tends to decrease from north to south, due in part to increased population density in the south and more favorable environmental factors such as reduced environmental variability, higher rainfall, and lower temperatures as compared to the north. In fact, reduced vulnerability to climate change is strongly linked to proximity to urban centers, such as Bamako, Sikasso, or Gao, a function of lower overall sensitivity and greater adaptive capacity to its impacts. In urban areas, increased water security and a lower proportion of households engaged in agriculture drives lowered sensitivity. Urban areas also have significantly higher adaptive capacity to deal with the effects of climate change, attributable to better access to essential services like finance, piped-in drinking water, electricity, and education.

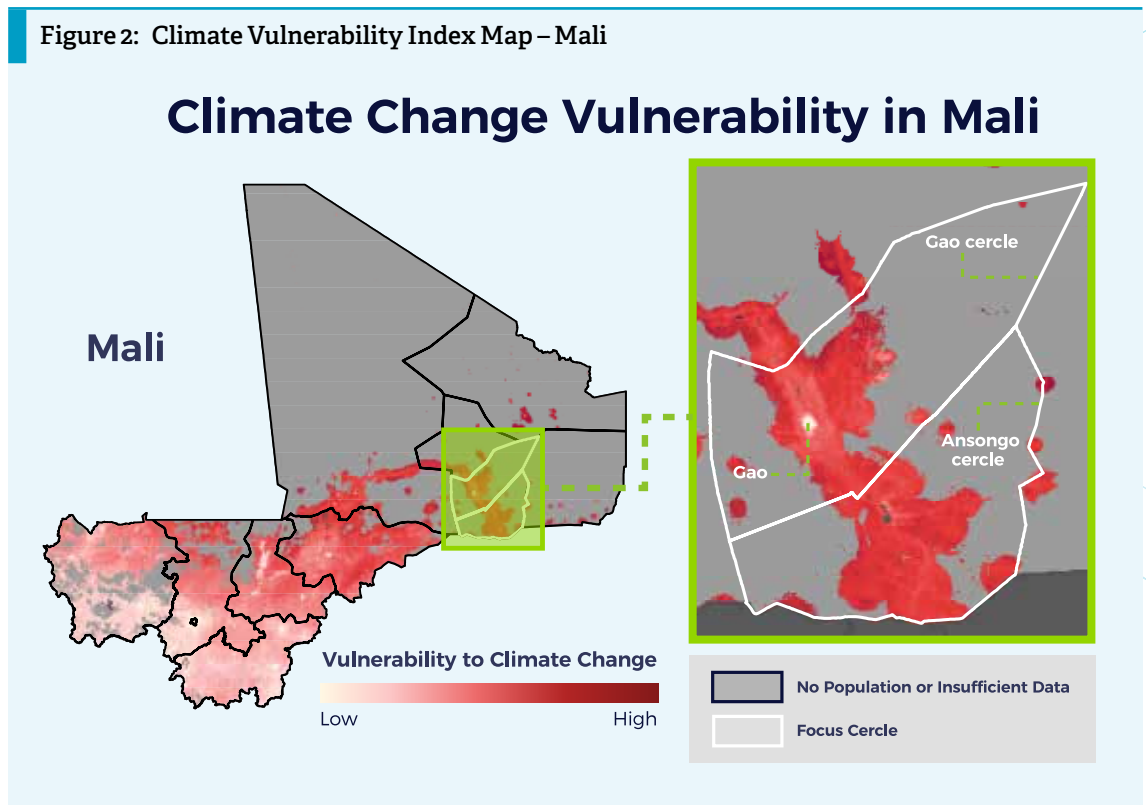
Profile

In order to maximize the practical implications of Fraym's indices, we narrowed our analysis to the *cercle*

level, Mali's second-level administrative division. Specifically, we examine two *cercles* in the Gao region (see Figure 2), among those included in USAID's Food for Peace (FFP) Development Food Security Activity (DFSA) for Mali (USAID 2020b).

Gao region's relatively low level of vulnerability overall hides a wide range of vulnerabilities within its broader borders. While Gao region ranks 5th out of Mali's 10 regions according to our vulnerability index, much of this is due to relatively low levels in its most populous Gao *cercle* (28th out of 50 *cercles* overall). Ansongo *cercle*, on the other hand, ranks 9th nationwide. We chose to investigate this disparity in greater detail. Although Gao *cercle* has relatively low levels of vulnerability, a large population makes this a good area to target for programs aimed at increasing adaptive capacity. Our team found that nearly 200,000 people, or about 53 percent of the population of Gao *cercle* have poor adaptive capacity, while about 215,000 people are highly vulnerable. ►

Figure 2: Climate Vulnerability Index Map – Mali



► While both *cercles* have similar levels of exposure and sensitivity, Ansongo *cercle*'s adaptive capacity is nearly 50 percent lower than Gao, signaling major gaps in human capital that proper programming may be able to address. In fact, over 95 percent of people living in Ansongo *cercle* classify as having both low adaptive capacity and high vulnerability to climate change. As the Food for Peace project implements its adaptive capacity-focused activities, AI/ML-produced hyperlocal data can be used to monitor progress toward improving household resilience from year to year. Moreover, a comprehensive human and environmental measurement of climate vulnerability—such as the one presented here—could be used to present the overall impact of the program on communities' adaptive capacity, adding a new dimension to impact evaluation for resilience programming.

Conclusion

Whether comparing trends within a district like Mangochi, or factors between low and highly vulnerable *cercles* like Ansongo and Gao, our approach reveals key regional differences in the subcomponents that define resilience to climate change. With a better understanding of vulnerability to climate change and its many components, implementers are better equipped to handle gaps in adaptive

capacity and reach vulnerable populations with greater efficiency and effectiveness. While case studies from Mali and Malawi show some similarities in terms of vulnerability, their differences highlight the need for a keen understanding of how socio-demographics and community responses to environmental change may affect participant outcomes. Having a better understanding of both baseline vulnerability and gaps in adaptive capacity can guide which indicators a program should track over time and the data collection efforts needed to meet monitoring requirements. ML can quickly and continuously monitor program areas, identify specific components of adaptive capacity, and evaluate how program activities are helping to address these gaps. The result is a more responsive program, able to effectively use project data for adaptive management.

Finally, this comprehensive approach to leveraging an immense amount of data using sophisticated AI/ML techniques can transform impact evaluation by measuring more without overburdening program participants with surveys and questionnaires, provide a more complete picture of the baseline and endline context in which program participants are living, and generate impact measurements that include environmental and human information in one measurement—such as climate vulnerability.

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Endnotes

1. Fraym is a geospatial data company that uses proprietary machine learning algorithms to deliver precise, local-level information. Its work primarily focuses on the continents of Africa, Asia, and Latin America.
2. While many components remain comparable between our models of Mali and Malawi, Fraym analysts intentionally altered some measures to reflect key contextual differences between the two countries and to produce as accurate a model as possible. For example, data and indicators in Malawi

were typically agriculturally focused, in line with research indicating greater dependency on agricultural income among poor and vulnerable southern-African households (Gbetibouo et al. 2009). However, poor and vulnerable households in Mali are typically dependent on livestock ownership as opposed to agriculture, especially in the northern, most arid parts of the country (Caffrey et al. 2014). Fraym's AI/ML technology enabled us to alter the indicators within the models to better reflect this and other local differences, without sacrificing in-depth analysis in either country.

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Integrating Big Data Analytics and Artificial Intelligence into Monitoring and Evaluation in a Fast-Changing Development Landscape

Recent advances in information technology resulting from the fourth industrial revolution and associated disruptive innovations have created vast quantities of big data, generated in real-time and in various formats. Associated developments, such as big data and artificial intelligence, have contributed to strengthening the field of monitoring and evaluation. Big data analytics and artificial intelligence technologies are playing a significant role in monitoring and assessment by increasing efficiency, reducing evaluation costs, and redefining the field of M&E. This article applies a decomposition framework to clarify big data analytics and artificial intelligence as determinants of monitoring and evaluation. It does so within the broader framework of disruptive technologies and the fourth industrial revolution and how they are shaping monitoring and evaluation.

Bernard Okpe, Nigeria Country Department, AfDB.

Key Messages

- The rise of the fourth industrial revolution (4IR) and associated boom in disruptive technologies have created novel platforms and tools that deepen citizen participation in decision making, allow citizens to easily access data and information, and enhance transparency and accountability.
- Big data and artificial intelligence have facilitated various capabilities (e.g., predictive modeling and large-scale forecasting) that are enhancing the processes of monitoring and evaluation of development operations.
- Big data analytics and artificial intelligence are essential tools that will contribute to achieving key indicators under the universal goals of the 2030 Agenda for Sustainable Development.

Introduction

Over the past decade, there has been increased competition for the limited resources allocated to international development, as opposed to the growing expectation of what ought to be achieved through such development assistance (Raftree & Bamberger 2016). This has spurred the demand for systems that can effectively evaluate the performance and effectiveness of development programs. The rise of big data analytics¹ and artificial intelligence (AI)² resulting from the fourth industrial revolution (4IR) and its associated boom in disruptive technologies have helped the development of platforms and tools that deepen citizen participation in decision making, and allow citizens to easily access information and services, thus improving transparency and accountability.

4IR refers to technological innovations characterized by a fusion of a series of technologies, which blur the lines between the physical, digital, and biological spheres. 4IR speeds up innovations, making

information access faster, more efficient, and more widely available. Technology in the era of 4IR is also increasingly connected, enabling societal shifts by influencing policy-making, economics, values, identities, and possibilities for future generations. Central to the 4IR is big data and AI (Manyika et al. 2013). However, a key issue of 4IR is how to effectively utilize technological advances to drive organizational performance (Nalubega & Uwizeyimana 2019). Disruptive technologies, on the other hand, refer to forms of innovations that tend to impact significantly and alter the traditional approach through which consumers, industries, and businesses behave (Segal et al. 2016). Disruptive technologies today play a significant role in the rise of new tools and techniques shaping the practice of monitoring and evaluation (M&E). For example, advances in mobile telephony have facilitated communication via text, social media and internet, in addition to voice calls (Segal et al. 2016). Additionally, mobile devices are increasingly being utilized as part of large-scale data collection efforts in many sectors, including ►►

► evaluation. Indeed, the widespread availability of smartphones, tablets, and other mobile devices, coupled with their multiple functionalities and decreasing cost of acquisition and operation, have transformed field data collection, processing, dissemination, and utilization efforts (Segal et al. 2016).

This article examines how big data analytics and AI impact the process of M&E. The article submits that these tools have managed to shape the process of M&E by triggering the development of more effective procedures and concludes that big data analytics and AI are essential for the future of M&E given how fast the development landscape is changing.

Big Data and Artificial Intelligence

Technology's growing capability to gather data associated with people's actions has prompted efforts to utilize such data to predict and track behaviors, as well as design fit-for-purpose development interventions. The boom in data has further advanced the development of AI. Technology mavens have quickly realized that analyzing data for purposes of improving decision making is tedious (Analytics 2018). Hence, they have developed intelligent algorithms to achieve the task of deriving insights from the vast data sets. Using the data generated from various sources, AI enables the building of a store of knowledge that aids accurate predictions (Russell & Norvig 2016). Further, the ability of AI to be integrated with big data has made the two technologies mutually reinforcing, given that the success of AI depends on the quality of data integrated into big data.

In AI, machines analyze data and adjust to new inputs. That is what enables the technology to be designed for specific interventions that enhance the process of evaluation (McKenzie 2018). Together, big data and AI are being used

to perform predictive modeling and to forecast large scale systemic changes. Development practitioners have also begun to explore the use of big data to predict as well as track behavior of individuals (Raftree & Bamberger 2016). One organization at the forefront of such research is the UN Global Pulse, which aims at establishing connections between the data generated by web users and possible development interventions. Another, Qatar Computing Research Institute, is filtering social media traffic to enhance disaster response (Raftree & Bamberger 2016). Today, it is widely accepted that high-quality development data is essential for development impact, as quality data is the basis for meaningful strategies that support policy-making, efficient resource allocation, and effective public service delivery. Concerns have, however, been raised about the ethical use of big data and AI due to their enhanced ability to predict people's behaviors and trends over space and time.

The Effect of Big Data and AI on M&E in Africa

Big data analytics and AI are no doubt prerequisites for the realization of the ambitious global goals of the 2030 Agenda for Sustainable Development since almost everything will be handled through technology. Indeed, related technologies such as satellite imagery, geo-engineering, and smartcards comprise of discoveries that have a high possibility of disrupting global development (Manyika et al. 2013). Other related technologies, such as virtual reality, are also being used in building models to support the M&E of development projects and programs as well as track the progress of development interventions both in Africa and globally. Similarly, these technologies are being used to evaluate interventions and facilitate service delivery as well as policy strengthening. ►

► In the field of M&E, big data has a high potential for complementing traditional data sources. The latter is accomplished by enhancing uniqueness as well as providing up to date information that can be utilized to present a comprehensive outlook of a situation (UN Global Pulse 2012). For example, remote reporting digital sensors can be used for evaluating by collecting objective data to enhance control of sustainability interventions. Conversely, others can track real-time occurrences by analyzing online content. This ability is necessary for providing a baseline for a current incident and updating this with current snapshots to monitor how a situation transforms, which can be used in the program interventions (UNDP 2013). Additionally, the UN Global Pulse operates several projects which utilize social media to monitor the social environment (UN Global Pulse 2012). This factor provides a baseline of how a public discourse changes over time to facilitate M&E of effectiveness.

4IR poses a challenge to the traditional M&E in both the public and private sectors. The technological advancements brought forth by the 4IR are changing how societies conduct their daily operations (CEPAL 2018). Besides the numerous opportunities associated with 4IR, it also poses a risk to the regulatory frameworks of countries from the perspective of data and cybersecurity, as well as consumer protection. There is, therefore, a need to address the effects of 4IR on M&E, both in Africa and globally. It also calls for an enhancement of the capabilities of evaluators to utilize the opportunities brought forth by the technological advancements to develop sustainable solutions (Rogerson 2014).

4IR provides vast opportunities for incorporating M&E into African and global development policies as well as program evaluation approaches. If appropriately done, M&E has a high likelihood of growing

and adapting to a changing environment while addressing worldwide public demands. Drawing on a case study from selected sectors in Kenya, the section below illustrates how big data can be used to improve M&E of projects. It highlights how big data and AI is shaping the transport sector, agriculture, and health service provision in the country. The influence of these technologies can efficiently help M&E to become more effective. They can also influence the development of better systems in those sectors.

Case Study: Application of AI and Big Data in Kenya

Ridesharing Apps – Uber, Taxify, and Little Cab in the Transport Sector

In Kenya, AI is applied in many areas, but this section focuses on its application in the transport industry. Kenya utilizes data about people's travel and use of taxi-hailing applications, such as Uber, Taxify, and Little Cab, to improve efficiency in the sector. According to Oduma (2020), AI has bridged the gap between travellers and service providers by gathering and mapping data such as routes with the most traffic congestion at specific times of the day. This data is used to guide motorists during peak hours, to enable them map out alternative roads. The system collects location data from the phones of people to find the most-used roads at different times of the day. It also uses news reports, blogs, social media posts, etc., to map-out details of the traffic conditions at different times of the day. Since many people use their phones while traveling, the system collects this data to find the times with the highest number of vehicles on the road. Also, given that some vehicles have geo-location services, the system draws on this geo-location information. These data/information sources enable the system to form a usable database regarding the condition of roads at different times of the day. ►

► **Implications for M&E.** Before the application of AI in this sector, travelers would spend a significant amount of time in traffic congestion since the drivers would not know the best route to use. However, after the commencement of using this technology, they have this information, which assists in selecting the best routes. Additionally, the government can now get details of the most congested roads and then find ways of easing traffic. This information can assist decision-makers, including M&E experts in the sector to decide on the existing road network to upgrade. The big data generated complements conventional evaluation methodologies as it provides cheap, quick, complexity-sensitive, longitudinal, and easily analyzable information that can be compiled into necessary information for M&E to improve the delivery of road infrastructure across the country. Moreover, before the deployment of AI in the transport sector, determining the roads that needed expansion was a tedious task that involved many evaluators who would move around searching for impact and potential roads for expansion. Therefore, AI has improved the transport sector in this country.

Smart AI-powered digital healthcare assistant

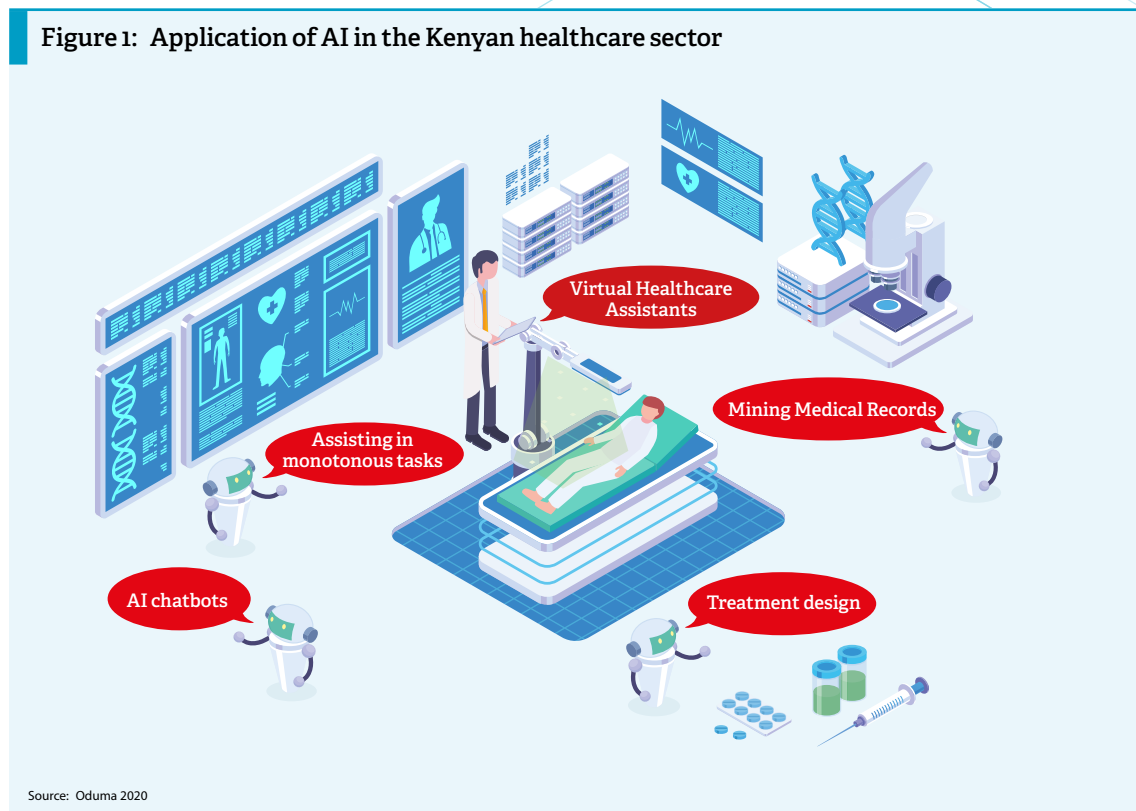
AI is also applied in the health sector in Kenya via the use of *Dr. Elsa*, a data-powered AI aimed at improving affordable and high-quality access to healthcare (Oduma 2020). Although the application of *Dr. Elsa* is still in its early stages in the health sector in Kenya, it is already improving service delivery—assisting in clinical decisions, diagnosis, and electronic health records (Guo & Li 2018). In the case of clinical decisions, AI helps health practitioners acquire and assimilate medical data. Without using this technology, the health sector would face a hard time keeping up with the large amount of data needed to create holistic assessments of patients, personalize treatments, improve communication, and enhance health

outcomes (Akannigbe et al. 2018). AI also helps in the diagnosis of patients: the number of errors in outpatient diagnosis in Kenya is high and AI is helping to reduce these. *Dr. Elsa* further allows patients to perform self-diagnosis of diseases based on their symptoms (Oduma 2020). Gradually, its use and uptake are picking pace. AI data used in this sector comes from many sources, including but not limited to: electronic health records that include the diseases that a person has, his/her symptoms, the prescribed medication, and the results of the treatment used; as well as laboratories where people get tested for different diseases. These sources provide a vital core database on symptoms and diagnosis. The system combines and studies the different data to determine relationships that can help future patients. For instance, when the system finds a relationship between a drug and its treatment outcomes, it can recommend them in future cases (Figure 1).

Implication for M&E. Big data and AI can help in the M&E of therapeutic techniques used in different health situations. For instance, practitioners can evaluate the effectiveness of a given drug and procedure used in treating a patient, which can be further enhanced with the use of AI and Big Data. Before the introduction of AI in the health sector, a significant amount of time was taken by practitioners to diagnose a patient. AI has helped in the detection of anomalies in the diagnosis of diseases and it helps practitioners to correct them. It also provides a better avenue to evaluators for a cheaper and quick way of mapping areas that are prone to some diseases. The information collected helps create opportunities for quicker and more targeted public health responses.

Drones in the Kenyan Agricultural Sector

AI is also improving agricultural production using drones. Drones are a powerful tool in geological, agricultural, ecological and forestry growth monitoring, as ►

Figure 1: Application of AI in the Kenyan healthcare sector

Source: Oduma 2020

► well as evaluation (Ren et al. 2019). As Oduma (2020) also notes, drone technology provides information regarding the quality of soil, the presence of pests, and nutrient deficiencies on farms. The use of drones helps farmers apply appropriate corrective measures, which allows their farms to have better production.

In Kenya several methods are used to collect drone data from farmers – smartphone applications, social media posts of farmers regarding the performance of their farms, and news articles. Also used are data from government agencies that test the nutrient level of soils in different areas, as well as market reports regarding the performance of agriculture in different parts of the country. The data generated are used to create descriptive maps that are fed into the drone’s GPS, which helps determine the areas that have defects based on the geolocation data.

Implications for M&E. These technologies help M&E in the agricultural sector

by allowing stakeholders to evaluate the effectiveness of the corrective approaches that they use. Drones have also been used in evaluations to map the extent of farm cover, assess the state of crops and soils over large areas – something that traditionally would have been both time and resource consuming, as well as labor intensive – requiring many people to assess the condition of a small area. So, in this way, the introduction of drones has made evaluating the agricultural sector faster and cheaper, and the evaluator can undertake large scale studies. Again, the use of drones facilitates appropriate corrective measures in the shortest time possible. Beyond aerial land coverage, drones are used to address pest infestations and weather-related issues. Although there are challenges with the application of drones – such as not every evaluator being able to afford it, or having the capacity to ‘fly’ one, these can be addressed through adequate planning and training of M&E experts. ►

Figure 2: Application of pesticides using a drone in Kenya



Source: Oduma 2020

► Conclusion & Looking Forward

To grow their economies and reduce poverty, countries across Africa require significant infrastructure investment in critical sectors such as education, technology, health, agriculture, and transport. However, better investment decisions require quality data. M&E is evolving, increasingly equipped with better technologies to support interventions for development results. This article suggests the need to utilize more big data and AI in M&E, and to develop appropriate infrastructure that will help leverage the huge opportunities presented by such technologies.

Clearly, the application of these technologies has opportunities and risks. First, a key opportunity is the improvement to several sectors—such as health, agriculture, transport, etc., as shown in the Kenya case. Second, these technologies present opportunities for improvement in productivity, support the work of M&E to track development results,

and allow governments and policy-makers to make informed decisions. Key risks associated with AI and big data focus on the safety of the personal information collected. Another risk is the ethics around the collection of personal data to build big data. Sectors that use these technologies need to ensure that individual data are protected (Cheatham et al. 2019).

Going forward, evaluators need to sensitize policymakers on how the results from big data and AI can be utilized in crafting better policies to inform development outcomes. Evaluators also need to transparently consider the associated risks and clearly state the safeguards adopted in terms of confidentiality protection and data governance. Besides, if big data is to be used in M&E, the same quality of standards used in data collection should be applied to improve reliability and consistency. Doing so will enhance the quality as well as the reliability of data captured by these technologies for M&E purposes even further than it currently happens.

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Endnotes

1. Big data as used here, refers to trends such as the volume of digital data produced daily as a result of high usage of digital services, new technologies and tools as well as methods to analyze large data sets (i.e., big data analytics).
2. Artificial intelligence alludes to a branch of computer science that facilitates the development of machines that can perform tasks that require human intelligence.

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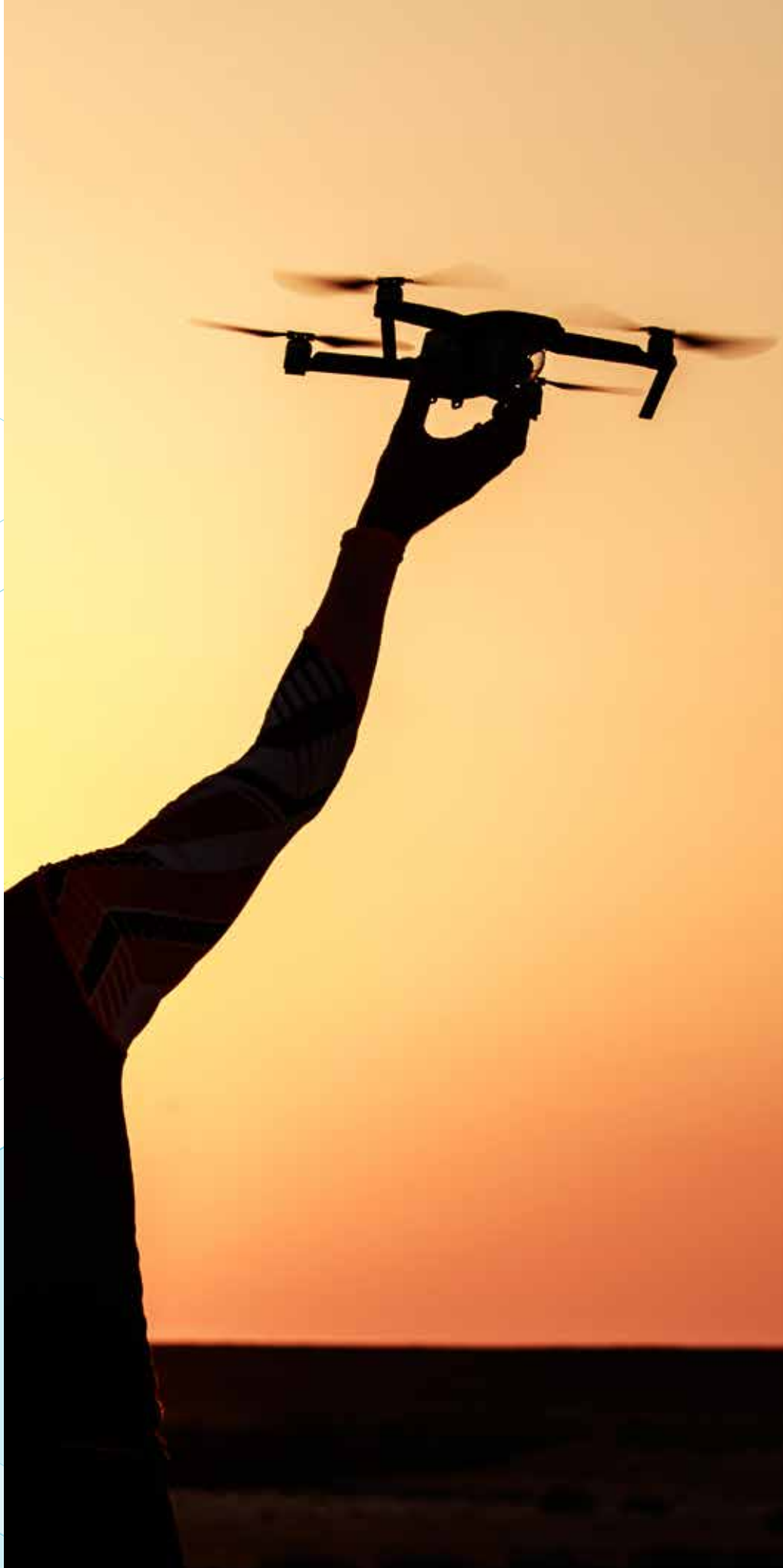
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Blog: Integrating Big Geodata & Technology in Evaluation:
What do we need to know?



Anupam Anand, Independent Evaluation Office, Global Environment Facility.

Key Messages

- Big geodata is a subset of big data with spatial information that derives from a rapidly expanding array of sources, including satellite data, ground sensors, and citizen science
- There are risks associated with using innovative technology. So, be prepared to embrace failures when innovative methods do not yield evaluative evidence.
- The challenge of a lack of resources and skills to process big geodata data, can be mitigated to an extent by using open datasets, free analytical tools and establishing partnerships.

Introduction

Great things happen when we cross disciplinary boundaries. With the amalgamation of knowledge and skills, collaborations between academic fields often are greater than the sum of their parts. I found myself on a similar journey where I negotiated the contours of multiple disciplines, starting as a geospatial scientist to being an evaluator at the Global Environment Facility–Independent Evaluation Office ([GEF IEO](#)).

This blog focuses on the application of big geodata, including satellite remote sensing, drones, and mobile phone-based technology, to the practice of impact evaluation. Big data is characterized by massive volume, is available at a rapid pace, and in a variety of formats that include both structured and unstructured data. Here I share some of the applications of big geodata and satellite technology drawing on my evaluation experience.

Applications in Evaluation

Leveraging big geodata: Big geodata is a subset of big data with spatial

information that derives from a rapidly expanding array of sources, including satellite data, ground sensors, and citizen science. In the [protected area evaluation](#), the GEF IEO used satellite data equivalent to billions of observations (pixels) of forest data for 35,000 protected areas across the globe averaging about 400 km² each. The satellite driven analysis enabled us to assess the effectiveness of GEF-supported protected areas compared to areas (buffer areas, other protected areas) that didn't receive GEF support. One of the key findings was that GEF-supported protected areas experienced much less deforestation compared to the adjacent areas that did not receive GEF support. This evaluative evidence was possible due to the availability of satellite data and the analytics to process it. The Beng Per protected area in figure 1 is an illustrative example of how the results looked for each of the 35,000 protected areas.

Use of high-performance computation: The GEF IEO made use of satellite data for assessing the effectiveness, impact, and sustainability of GEF interventions in land degradation, climate change, international waters, and biodiversity thematic areas. Analysis of satellite ▶▶

Figure 1: Satellite data analysis showing deforestation (red) around Beng Per protected area (2001-20018) in Cambodia



Source: Anupam Anand/GEF IEO

► data at a large scale requires the use of high-performance computing generally not available in evaluation offices. By using existing computing resources innovatively, this challenge can be mitigated easily. For instance, I made use of parallel computing utilizing multiple cores already available in most modern desktops and laptops. This setup helped assign the computing task to multiple processors that efficiently distributed the task and hence drastically reduced the computing time. The process of parallel computing takes minor modifications in programming language codes and is supported by most statistical packages such as R, Python, and Stata. For scaling up the analysis, the GEF IEO collaborated with the University of Maryland (UMD) and NASA.

Use of machine learning (ML) and artificial intelligence (AI): The GEF IEO has also been leveraging machine learning and

artificial intelligence for satellite data classification and running complex regressions. Machine learning algorithms are data-hungry and work very efficiently with big geodata, including satellite imagery. The GEF IEO used ML and AI for analysis of satellite data and for identifying the factors associated with impact assessed through variable importance of the ML regression model.

Use of drones: Drones are handy for doing rapid assessments in hard to reach, isolated, and unsafe areas. I have used drones to assess the extent of [illegal mining](#) and logging areas at different project sites (figures 2 & 3) and to collect ground truth data for validating satellite data products. The fun part of using drones is the ability to use them to capture visuals that can later be used to enhance knowledge and learning products. Here is an [evaluation summary](#) prepared by using videos and images captured by drones. ►

Figure 2: Drone being deployed from a remote road



Source: Anupam Anand/GEF IEO

Figure 3: Drone image of an illegal mining site



Source: Anupam Anand/GEF IEO

► **Mobile devices:** The GEF IEO has used open-source data collection tools deployed through smartphones to capture field information efficiently. Mobile devices can be used to obtain information from various sources - audio, video, text, and location information (GPS data) in a structured and efficient way (figure 4). In the evaluation of GEF-supported [land degradation interventions](#), I used qualitative data collected through smartphones to triangulate the findings from fieldwork and the satellite data analysis. I used the stakeholder interview data to answer the “Why” questions while the satellite data helped us to know the “What,” “Where,” and “How Much” of environmental change.

Lessons learned and the way forward

Drawing on the GEF IEO experience, I have highlighted some challenges and lessons for integrating the use of these innovative tools and data into evaluations.

■ **Questions first:** It can be overwhelming to choose from the extensive suite of tools and data available while getting excited at the prospects of their use and potential results. However, designing the right questions for the evaluation

is the essential first step to generate useful information and not the other way around.

- **Identify the low hanging fruits and opportunities:** Big geodata has proven its usefulness in specific contexts outside the evaluation community, especially in isolated, hard to reach and remote areas, conflict zones, and regions hit by natural disasters. Remote sensing technology can be particularly helpful considering the current pandemic, when restricted travel has posed methodological challenges for evaluators. The technology can also be applied in conflict and disaster zones for planning, monitoring, and evaluation.
- **Need for multidisciplinary teams:** Although the terms big data and innovation are used as singular nouns, successful implementation needs a suite of tools and multi-disciplinary teams. The data scientist might be an expert in one domain, but subject matter expertise in evaluation is crucial for the successful integration of these methods and datasets into the evaluation. Knowledge about the evaluation helps set the right questions, and knowledge about the use and caveats with data and methods help ►

Figure 4: Use of mobile device-based survey to triangulate findings from satellite data analysis. The satellite data shows the restoration of the forest area during the intervention (upper panel). The lower panel shows a smartphone-based survey and a snapshot of the survey form



Source: Anupam Anand/GEF IEO

- ▶ integrate these within the evaluation. It is, therefore, essential to work with a multidisciplinary team right from the planning stage for the assessment through to its execution, analysis, and interpretation of evaluative evidence.
- **The resource implications:** Evaluation budgets must account for both human and financial resources needed for the integration of big data and tools. These include additional costs in hiring technical experts, and acquiring hardware and software required to conduct analyses. One must be creative in managing costs. Collaboration with academic and specialized institutions and the use of open data and free tools, including for machine learning, come handy. As mentioned before, the GEF IEO has collaborated with the National

Aeronautics and Space Administration (NASA) and the University of Maryland. The GEF IEO often uses open source software such as R, QGIS, and python for accomplishing critical tasks.

- **Risk and failures are inevitable:** There are certain risks associated with the use of innovative technology because there are not too many “how-to” guides available. For instance, a satellite data analysis might not show a significant difference as a result of an intervention. The reason could be simply that the activities made no difference on the ground. However, it could also be due to the limitations of the satellite to pick changes at a granular level (figure 5). If the latter, one should try to address it when possible, but also be prepared to embrace failures when the use ▶▶

Figure 5: High-resolution image (left) captures the drivers of deforestation vs. low-resolution image (right) which doesn't provide as much detail



Source: [PA Evaluation/ GEF IEO](#).

- ▶ of innovative methods do not yield evaluative evidence.
- **Continuous learning is the key:** The field of big data and technology is growing at a rapid pace, and therefore integrating it with evaluation methods will be a dynamic learning process as new data and tools will continue to emerge. Therefore, continuous learning is the key while keeping evaluations anchored on a strong theoretical basis and asking the right questions.
- **Cost considerations can be a challenge, as well as an opportunity for the global south:** Free raw satellite data is increasingly available on a global scale. However, the challenge for the

global south lies in the lack of resources to process big geodata data and the adequate skill sets to do so. These can be mitigated to an extent by using [open datasets](#) and free analytical tools and establishing partnerships with national research organizations. Regarding skills and professional development, Massive Open Online Courses (MOOCs) offered by reputed organizations and universities on data science and geospatial capabilities are available free of charge to anyone with a good internet connection. Evaluation forums have also begun to provide training on innovative methods through workshops. The knowledge is out there, and one needs creative ways to tap into it and apply it.

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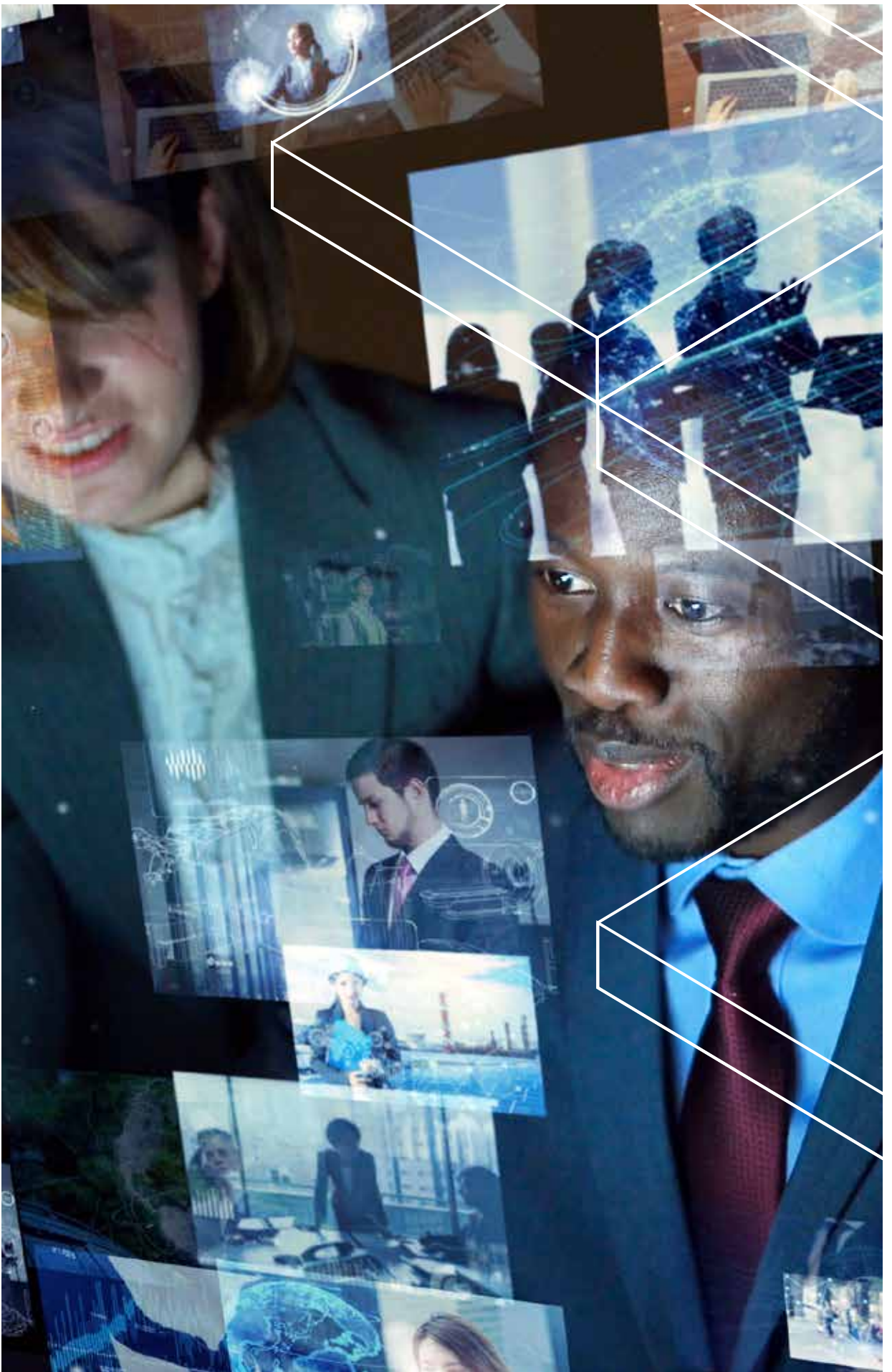
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Author's profile

Anupam Anand is an Evaluation Officer at the Independent Evaluation Office of the Global Environment Facility (GEF IEO). With more than 14 years of combined experience in evaluation, international development, academic research, and teaching, he has led evaluations on biodiversity, land degradation, Nagoya protocol, and illegal wildlife trade while supporting several other evaluations with geospatial and field research. Anupam uses a blend of innovative approaches such as satellite data, GIS, machine learning, computational social science, drones, and mobile-based field surveys together with qualitative methods to enhance evaluative evidence and knowledge products. Before IEO, he was a Remote Sensing Scientist at the Global Land Cover Facility (GLCF), University of Maryland working on multiple NASA funded projects including field campaigns for future satellite missions, and has consulted for the Climate Investment Funds, World Bank. Anupam holds a PhD in ecological applications of remote sensing, particularly the Lidar sensor from the University of Maryland. He has published several peer-reviewed articles and book chapters broadly related to remote sensing, ecology, sustainable development, land cover change, and environmental policy.





Disruptive Technology and Innovations and Big Data Shaping Evaluation of Governance in Africa

Big data and disruptive technological innovations (DTI) are increasingly shaping and redefining how to evaluate governance in Africa. While invaluable, evaluating the impact of disruptive technologies on governance is not widespread. This article submits that notwithstanding some concerns and skepticisms about the role of DTI and big data on governance processes, there is no denying that DTI facilitate the exchange of information that is vital to the promotion of efficiency in various aspects of life, including the governance and political arena.

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Key Messages

- Disruptive technologies and innovations are radically transforming governance processes globally.
- Although disruptive technologies play a critical role in helping with accomplishing improvements in policy making and efficiency in service delivery in areas such as agriculture, education, and healthcare, these achievements come with great risks and costs.
- Addressing the risks associated with disruptive technologies will entail a process whereby the data for evaluation is unbiased and of high quality, and involves updating of existing rules and regulations in the use of new technologies.

Introduction

One of the significant developments over the last two decades has been the emergence of various forms of information communication technologies (ICTs). Brennan, Subramaniam & van Staden (2019) have pointed out that disruptive technology and innovations (DTI) and other technological advances such as artificial intelligence (AI), the Internet of Things (IoT) as well as big data¹ have led to unprecedented changes, often disrupting the way services have traditionally been produced and consumed. Additionally, they note that the ability to handle large volumes of digitized data in rapid and complex ways through these technologies has also increased our dependency on more open, multi-platform, networked structures. The issue that crops up is how these new developments are redefining how we evaluate the impact of DTI on Africa. DTI has contributed to the process of data being collected in real time, meaning that we are able to assess information in real time and react as such. However, as Mackenzie (2018) argues, data collection is

not error-free, so if you make a prediction based on error, but the reality is different from the data being shown, there arises the issue of which one is the error.

One area which researchers have become interested in, is evaluating how DTI and big data are impacting the governance process.² However, Hermanns (2008) argues that detailed analysis of possible effects of DTI on politics are scant. As he contends, “there are far fewer publications in the political science literature on the impact of mobile phone technology on politics and political behavior” (Hermanns 2008: 75). Moreover, the available literature deals with the role of DTI such as social media in Western democracies, with less emphasis being placed on the debate concerning emerging democratic environments and developing countries (Wolfsfeld, Segev & Sheaffer 2013). Thus, evaluation of new DTI on governance, which is an important part of the process of providing valuable information to support the decision-making process (Sukai 2013: 77) is lacking in the African context. Undertaking an evaluation process in an independent and context-specific way is critical to realizing the success that most models aspire ➤

► to (Segone et al. 2013: 8). Against this backdrop, this article examines how DTI is shaping and redefining how we evaluate governance in Africa. Specifically, it seeks to answer the following questions: What are the benefits of DTI on the broader governance landscape in African societies? What are some of the costs and concerns associated with the pervasive use of DTI and big data in governance? In answering these questions, the article's thesis is that although DTI and big data enable governments and citizens to organize themselves at little cost, and the world is able to bear witness as well as facilitate the exchange of information that is vital to the coordination of various activities, the use of big data and DTI for negative purposes such as spreading misinformation and authoritarianism by governments cannot be underestimated.

DTI, Big Data & Governance

The disruption of traditional ways of communication and information exchange is a consequence of the rise of a new and powerful business model (mass data). According to Körner (2019), the spread of the data economy has become almost universal, as cheap access to smartphones and free content have made online behavior independent from people's financial, ethnic, religious and political background. In the political and governance realm, DTI are playing a crucial role in shaping various political activism taking place in much of the world. Körner (2019) adds that people enjoy access to information that was unimaginable just a few decades ago, and the possibility to exchange and coordinate themselves worldwide in a matter of seconds. For billions of people, the digital transformation with which the smartphone is synonymous has brought enormous benefits and convenience—notably it has enriched societal discourse via new forms of multilateral communication. Agrawala (2019) opines that digital transformation and the concomitant availability of more data

can improve policy design and making by lowering the cost of policy experimentation and evaluation. This view is shared by Nalubega & Uwizeyimana (2019) who contend that the innovations and technological advancements of the fourth industrial revolution (4IR) are uprooting and changing how societies do business and go about their daily work. These innovations and technological advancements have been referred to as a set of disruptive technologies that are transforming social, economic, and political systems, and putting pressure on leaders and policy-makers globally.

Likewise, DTI such as drones have been used to improve health care in countries like Rwanda and Tanzania, and most recently Ghana. Similarly, Massive Open Online Courses (MOOCs) have been employed to improve access to education in universities such as the University of Lagos, University of Cape Town, University of the Witwatersrand and Stellenbosch University (Nalubega & Uwizeyimana 2019). In the labor market, the growth in AI, coupled with machine learning, while transforming the workplace, also free up the need for human labor. AI has made it possible to automate a range of tasks by enabling machines to play an increasing role in drawing conclusions from data and then acting. Kahne & Bowyer (2018) also noted that increased technological advancements have resulted in the internet becoming a dominant force when it comes to how campaign funds are raised, outcomes are evaluated, perspectives are shared and discussed, and individuals are mobilized to act politically. The most fascinating ability of DTI such as social media is that it enables ordinary citizens to connect and organize themselves with little to no cost, and the world to bear witness. Social media such as Facebook and Twitter have become standard evaluation tools for citizens, representatives and governments to reach out to each other and exchange views, opinions and policy proposals (Körner 2019; see also Jotia 2018 on the Arab Spring). ►►

► Criticisms and Limitations of DTI & Big Data

Notwithstanding the benefits of the digital transformation, which has led to unprecedented access to and exchange of information for human communication and organization over the past years, Körner (2019) points out that digital technology has also amplified the spread of misinformation, echo chambers, and propaganda, thereby possibly contributing to rising populism and the polarization of democratic societies. Users across the globe enjoy 'free' services in the data economy, but underlying business models and a concentration of influence and wealth have raised pressing questions regarding privacy, data ownership and targeted manipulation for both economic and political purposes. For Körner (2019), the combination of big data and AI give governments unprecedented means to monitor, surveil, control and influence their citizens. For authoritarian states, these tools can help detect and prevent any kind of dissent at an early stage and prevent the formation of opposition and civil right groups that could challenge the concentration of the political and economic power of a ruling elite. As authoritarian governments can enforce access to all information and data collected and stored by private companies (which are often not clearly separated from the government anyway), the state's means of monitoring and control can comprise all aspects of citizens' lives (Körner 2019). Additionally, digital technology can also be used in established democracies to deliberately manipulate voters and distort the political discourse. Authoritarian states have also quickly learned to use surveillance technology, mass data and artificial intelligence to their advantage, both for domestic control as well as the erosion of democratic societies abroad. The continuous spread of conspiracy theories and other factually incorrect or highly biased information undermines

citizens' ability to identify and evaluate 'objective' or shared truth (Körner 2019).

To Agrawala (2019), while the availability of more data usually contributes to improvements in policies, it is not a panacea and comes with risks that will need to be tackled over the next decade: in some instances, less data is better than more. Particularly, digital transformation poses several challenges: the increased granularity of data and increased data-sharing between government agencies and across public-private partnerships can generate digital security vulnerabilities and concerns over individual privacy. Similarly, for Nalubega & Uwizeyimana (2019), the issue of privacy and data security, for example, is contentious as it regards the adoption of some disruptive technologies for data collection. Using phones to track daily movements and communications among people, analyzing people's moods on social media and using drones and geo-spatial tools to photograph private properties create a worrying environment for privacy in a community – and raise serious ethical questions for evaluation based on DTI. There is an increasing fear of trading of data, and this may spark conflicts and misunderstandings. Monitoring and evaluation (M&E) personnel and departments have the challenge of ensuring that the collected data is safe from malicious acts; otherwise, it can put the individual or the entire country at risk or in a state of vulnerability. Moreover, with the adoption of some technologies, some key data may have strict and/or limited access, thus hindering extraction for analysis. Lack of critical data because of limited access can create a challenging situation for M&E personnel and departments. The complexity of the ethical issues pertaining to the deployment of disruptive technologies is also a huge challenge for the African public sector. Furthermore, in big data analytics, predictive analytics are emphasised, which contrasts ►

▶ with the experimental designs often employed in the current public sector M&E. Also, using big data from disruptive technologies solely to draw evaluation recommendations may be quite misleading as such data have a significant selection bias (Nalubega & Uwizeyimana 2019).

Another issue is that the increasing growth in mobile technology and rise in disruptive innovations in Africa have implications for labor employment, and raise the question of whether data scientists will encroach on the livelihoods and profession of evaluators. The technological transformations, while creating novel possibilities, again raise concerns about existing legal and regulatory frameworks in an emerging context. How are evaluators expected to navigate the emerging ecosystem, given that the data used by evaluators will be generated, controlled and disseminated in novel ways and formats (e.g., big data, block chain), and there are multiple actors involved with regulation, marketing and generation of data (e.g., drone technology, machine learning, AI, mobile apps, new social media, etc.)?

In the political arena, while it is often assumed that DTI such as social media are an effective tool in getting people to be easily involved in the political process and to improve political activism, Kaplan and Haenlein (2010) take a contrary view. They highlight how the use of social media has the potential of not only undermining representative government but also to create 'depoliticization.' They demonstrate how people can organize themselves to plan activities directly instead of working through their elected governments and other official representatives. Additionally, Rød & Weidmann (2015) have called into question the perspective that improvements in ICT, as embodied in the internet, have contributed to a global shift towards democracy, political participation and activism. They argue that the role of social media in recent popular uprisings against Arab autocrats has fueled the

notion of 'liberation technology', namely that ICT facilitates organization of antigovernment movements in autocracies. For them, less optimistic observers contend that ICT is a tool of repression in the hands of autocrats, imposing further restrictions on political and social liberties.

Moreover, DTI as evidenced in social media, according to Allcott & Gentzkow (2017), create small, deeply polarized groups of individuals who tend to believe everything they hear, no matter how divorced from reality, as well as help foster an environment that enables those who are bent on creating and sustaining a divided and polarized society to continue. Allcott & Gentzkow (2017) add that social media has thus become the outlet through which "fake news," which they define and conceptualize as intentionally and verifiably false news articles as well as distorted signals uncorrelated with the truth, can be delivered. As Persily (2017) points out, it is because of such concerns that several internet platforms (e.g., Google, Facebook, and Twitter) changed their policies concerning information on their sites to address perceived shortcomings of the communications environment. Finally, apart from internet connectivity facilitating digital censorship and the identification and arrest in authoritarian regimes of individuals critical of political power holders (Rød & Weidmann 2015), a critical limitation of political information found on social networking sites is the lack of quality and reliability – something that poses a challenge to evaluation.

Addressing DTI Concerns: The Way Forward

The 4IR is thought to bring about enormous benefits associated with increased efficiency and effectiveness in service delivery, including the highly anticipated opportunities related to automated and digital transformations (Nalubega & Uwizeyimana 2019). ▶

► Notwithstanding the benefits, as noted earlier, the growth in DTI comes with challenges for evaluation. So how should evaluators and policy-making elites, who are increasingly placed on the back-foot, address disruption, innovation and technological change? (Hasselbalch 2017). As Hasselbalch (2017) states, innovations often lead to accelerating changes, disruptions, and fundamental challenges for the economy, society and policy-makers that demand sweeping regulatory responses. It is in this regard that Nalubega & Uwizeyimana (2019) indicate that governments in African countries need to understand the challenges associated with DTI and thus adopt measures to mitigate the impact of the unpredictable and rapidly changing products and services created for the public. Similarly, the speed with which DTI is evolving calls for evaluators to anticipate and plan appropriately to respond to the changing landscape so as not to be caught flat-footed and be overtaken by developments. Indeed, it is because of some of the problems and concerns with DTIs identified above that an Afrocentric approach to evaluating the impact of digital technologies in the governance process in Africa has increasingly gained attention. Having an evaluation model that takes into consideration the contextual and institutional factors of the society represents an important aspect of helping that country achieve its objective of realizing independent evaluation tools and approaches. It is important that various stakeholders broaden their horizon and knowledge base regarding the role that technology plays to understand not only its benefits, but also its risks in order to succeed.

Also, given that it is extremely important to get the governance arrangements of disruptive innovations 'right,' Hasselbalch (2017) suggests that there is a need to gather information on the nature and expected impacts of the disruptions in order to figure out what is being looked at.

In this vein, rather than just focusing on impact assessments, we should consider the full range of assessment exercises, as well as the highly political games that go into choosing between assessment regimes, organizing evidence and data within them, and dictating for what the assessments are used. Moreover, we should imagine and describe new forms of assessment, such as innovation assessment, that can rise to novel regulatory challenges (Hasselbalch 2017). To this end, Körner (2019) points out that governments need to update regulation, competition rules and supervision to account for the transformed requirements of the data economy. Companies need to ensure that their business models and products are compatible with constitutional rights and the integrity of democratic institutions and processes. Evaluators need to better understand the algorithms and designs behind their apps and devices as well as the mechanics of the data economy. Societies need an informed dialogue on data and technology ownership on how to share the fruits of technological progress and on how to prevent increasing asymmetries in wealth and power from destabilizing their foundations.

Significantly, as Nalubega & Uwizeyimana (2019) argue, in current M&E systems, substantial efforts are dedicated towards ensuring that the data to be used are unbiased and of high quality. The use of data from some disruptive innovations poses the challenge of having what can be termed an 'early warning signal' for crises to masquerade as the real data evaluators may use to draw conclusions on the impact of a given occurrence, program or policy that may have serious consequences. It is therefore important in the 4IR to clarify what qualifies as a 'warning signal', to conduct research and to distinguish them from M&E. Finally, maximizing the opportunities in the 4IR requires multi-stakeholder efforts that call for an open mindset to fully explore the contributions from innovative ideas. ►

► This might require deep integration, or collaboration on long-term technology, to efficiently manage and control the highly complex and interdependent nature of the disruptive innovations. In the 4IR, it would be no surprise if some of the most powerful solutions to the challenges faced in Africa come from small start-ups or simpler collaborations rather than traditional large set-ups of public management. Therefore, emerging policies aimed at regulating or guiding the 4IR innovative technologies need to be adaptive, inclusive, sustainable and human-centered in order to address the increasing challenges of these new technological changes (Nalubega & Uwizeyimana 2019).

Conclusion

The focus of this article was on the role of DTI, big data, and their evaluation

for governance in the African context. It noted that the use of DTI and big data can assist in effective and efficient evaluation of policies. The article argued that notwithstanding the concerns and skepticisms regarding the role of DTI and big data in the governance process such as helping with political mobilization and activism, there is no denying that DTI facilitate the exchange of information that is vital to the promotion of efficiency in various aspects of life, including the governance and political arena. Apart from DTI such as social media platforms facilitating the exchange of emotional and motivational contents in support of and opposition to protest activity, including messages emphasizing anger, social identification, group efficacy, and concerns about fairness and justice, their role in improving policy design through lowering the cost of policy experimentation and evaluation, is equally significant.

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Endnotes

1. To Emmanuel & Stanier (2016) big data is the collection, processing, analysis and visualization of large volumes and a variety of structured and unstructured data sets that are difficult to process using traditional database and software techniques.
2. Fukuyama (2013) defines governance as a government's ability to make and enforce rules, and to deliver services, regardless of whether that government is democratic or not. He notes two separate dimensions of governance: capacity and autonomy. The quality of governance is ultimately a function of the interaction of capacity and autonomy, and either one independently will be inadequate as a measure of government quality.

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Agricultural Institutions and Policies: Disruptive Technology and Evaluation Research in Africa

Agricultural institutions and policies occupy a pivotal place in Africa's development trajectory, because of the importance of the sector to political, economic and social relations. This article, against the backdrop of evaluation research, examines the role of disruptive technology in agricultural development – using the New Rice for Africa (NERICA) project as a case study. The article concludes that disruptive technology and evaluation research must bear in mind the complex interaction between the producers and users of knowledge and recognize their common interests and goals.

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Key Messages

- African agriculture has no shortage of institutions and policies, but there is a lack of political commitment in terms of access to resources.
- Disruptive technology is not the magic bullet for evaluation research in African agriculture.
- Technology functions in a social and political context and its usefulness in development planning and evaluation is subject to both technical and non-technical considerations.

Introduction

The role and importance of institutions and policies in social change have been accepted as a universal statement of faith. Institutions provide the framework through which policies can drive the broad social agenda. As North (1990) points out, institutions offer the “rules of the game”. In the African situation, agricultural institutions and policies occupy a pivotal place in the region’s development trajectory, because of the importance of the agricultural sector to political, economic and social relations. Thus, the African state and external actors, as such development partners, have since the postcolonial era set up and initiated agricultural institutions and policies (ACBF 2012; Pupilampu 2003). Indeed, there has not been a shortage of agricultural institutions and policies in African development. The problem, however, is “desirable policy and institutional outcomes in the face of available resources, because political commitment, although necessary, is a not a sufficient condition” (Pupilampu and Essegbey 2018: 65). If political commitment is not a sufficient condition, what then would account for desirable outcomes of African agricultural institutions and policies?

It is generally known that technological changes are indispensable to the rational

outcomes associated with developed societies, and that developing societies should employ technology in a significant way in agricultural institutions and policies to hasten national development. This article, against the backdrop of evaluation research, examines the role of disruptive technology in agricultural development. The analysis is based on the institutional and policy processes of the New Rice for Africa (NERICA) project. The article argues that technology is not a disembodied entity, but rather functions in a social setting that shapes the technology just as the technology also shapes society. Hence, technological changes require agency, and the outcomes are contingent and not predetermined. The article is structured into four parts: the first outlines salient aspects of agricultural development, disruptive technology and evaluation research. The second section presents the NERICA project. Section three is about analysis, and the last section concludes.

Agricultural Development, Disruptive Technology and Evaluation Research

Since the early postcolonial era, mechanization programs, as part of modernizing agriculture, were an integral feature of development plans in ►►

► many African countries. These programs, however, did not dramatically improve agricultural development in Africa, due to political and non-technical factors (Griffin 1979) such as the cost of technology—in effect, its social situation. The question then becomes whether the character of disruptive technology is so unique to transcend non-technical issues and more useful to agricultural institutions and policies in Africa. Disruptive technology, popularized by Christenson (1997), is an innovative process that zeros in on how technological changes give rise to novel outcomes that can have consequences for institutional and policy evaluation. The driving force in the process is the advances in communications and information technologies, such as smartphones, global positioning systems, satellite imagery, data transmission, and artificial intelligence that have collectively given rise to the Internet of Things (IoT).

IoT involve interconnectivity of physical and virtual communication systems in which “items in the physical world, and sensors within or attached to those items, are connected to the Internet via wireless and wired Internet connections” (Ndubuaku and Okereafor 2015: 23). Bringing IoT to bear on agricultural institutions and policies has led to notions such as smart agriculture, digital agriculture and smart farming as critical aspects of the future of agriculture (Bacco et al. 2019; Eitzinger et al. 2019). Digital agriculture includes the use of robots, real time data collection and analytical systems that are amenable to measurement and careful calibration to ascertain outcomes. Digitalization can shore-up African agriculture and has the potential to improve institutional and policy outcomes, issues at the heart of evaluation research.

Evaluation research has an interest in policy or program impact, explicitly an analysis of whether policies or programs are attaining goals and objectives. According to Langbein (2012:3), evaluation research

includes “the application of empirical social science research to the process of judging the effectiveness of... policies, programs, or projects, as well as their management and implementation for decision making purposes”. Evaluation research, especially in the case of agricultural development, raises questions such as what is working or not working and why; and how impact or effectiveness can be attained. There are issues of measurement involved in program or policy assessment, especially in the case of program evaluation. This kind of evaluation, as the name implies, is “directed at answering the question of whether a program, policy, or project worked” (Symbaluk 2014:271). It is the policy measurement processes in evaluation research that best demonstrate the role of technology, and in this case disruptive technology. Disruptive technology will make it possible to monitor outcomes, because of its physical attributes, including sensors that can be programed for measurement and to generate the required data for subsequent analysis.

NERICA Project in West Africa: A Brief Overview

The agricultural sector in Africa has been the site of significant changes, especially with reference to technology and the role of the state (Satgar 2011; Puplampu 2006). All three sectors of agriculture—production, marketing and consumption—have experienced technological changes. Take the case of production, where contract farming systems involve technology as both a means and an end, introducing “distinctive work routines” (Watts 1990:149) and agricultural goods suitable for global supply chains respectively. Technological changes in production are best exemplified in the case of rice, a staple food in many African countries. There is a shortfall between domestic rice production and consumption, making it necessary for rice imports to meet increasing demand. According to Atera et al. (2011:60), “sub-Saharan Africa ►

► produced about 21.6 million tons of rice in 2006 and accounted for 32% of rice imports in the global international market to meet its demand”. The antecedent for rice imports can be traced to the low rice yield from domestic production due to several factors, ranging from seed varieties, differences in agro-climatic conditions, to the nature of agricultural research (Arouna et al. 2017). These factors spurred the Africa Rice Centre, an affiliate of the Consultative Group on International Agricultural Research (CGIAR), into a novel research plan that eventually led to NERICA (Otsuka and Kijima 2010).

The NERICA research focused on inter-specific hybridization between *Oryza glaberrima* (African rice) and *Oryza sativa* (Asian rice), and the goal was to combine traits from the African variety, which is resistant to pests, weeds and difficult soil conditions, with the Asian variety, which is high yielding and ideal for mineral fertilization. Beginning with experiments in 1991, rice varieties were available by 1994 “through perseverance and the use of biotechnology tools such as anther culture and embryo rescue techniques” and this gave birth to NERICA (Diagne et al. 2011:255). By cross-breeding high-producing Asian plants with African varieties that thrived in the region’s poor soils and drought conditions, the significance of NERICA is the increase in yields of up to 250 percent while cutting growing time in half for rice farmers, potentially providing 240 million people with more food in West Africa and beyond (World Food Prize 2020). The new and improved varieties were subsequently adopted by farmers in many African countries, notably Burkina Faso, Gambia, Ghana, Kenya and Uganda (Atera et al. 2011; Diagne et al. 2011).

Farmers adopted NERICA because the research methodology allowed them to choose from available crop varieties. Indeed, farmers were persuaded about their role in the development and dissemination of crop varieties, they were

key participants in site-specific factors like agronomic and selection options (Diagne et al. 2011). The methodological orientation of NERICA made a major difference in its widespread utilization, in the sense that it made farmers co-knowledge creators in agricultural research (Kilelu, Klerkx and Leeuwis 2013). The implications of NERICA for food security in Africa have been rightfully noted (Anderson and Jackson 2005). The Africa Rice Centre and its director (Monty Jones) won CGIAR’s King Baudouin Award in 2000 and the World Food Prize in 2004 (with Yuan Longping, from China) (CGIAR 2020; World Food Prize 2020). NERICA, beyond its potential to feed millions of people in Africa, also aligns with both disruptive technology and evaluation research.

The NERICA Project: Disruptive Technology and Evaluation Research

NERICA was a niche product suitable to the agronomic and social conditions of rice farmers in Africa. The disruptive aspects of NERICA can be attributed to two inter-related factors, first, the enhanced technological aspects of the crossbreeding process and second, the adoption rate and success in several African countries due to the methodological orientation of the research project. As an inter-specific hybrid, NERICA has several improved ‘lines’ which African rice farmers have adopted in various agro-climatic conditions. As Somado et al. (2008) show, NERICA is an extended family of various ‘lines’ and that means the agro-physiological traits of NERICA are not homogenous, giving rise to different varieties adopted or released in many countries. The emergence of the multiple ‘lines’ are technical processes embodied in novel techniques that are disruptive in nature and character.

The variety of the traits, in turn, account for the successes in adoption across Africa. Certainly, the technical details ►►

► associated with each NERICA trait are easily discernable and farmers' preferences can also be clearly identified and specified. Farmers in Côte d'Ivoire and Nigeria prefer NERICA 1 and 2, Guinea farmers adopt NERICA 1 and 6, and Mali and Uganda farmers opt for NERICA 4 (Somado et al. 2008). Atera et al. (2011), in a statistical study on the field evaluation of NERICA in western Kenya (NERICA 1, 4, 10 and 11), documented the superior qualities of NERICA compared to the traditional rice varieties in the region. Kijima et al. (2006) also found potential yield increases of NERICA compared to other varieties in Uganda. What is significant about these evaluation findings is the recognition of non-technical factors like the experience of the rice farmers, seed distribution and the availability and timing of fertilizer; in sum, conditions of access to relevant agricultural inputs.

Evaluation research and its focus on policy can shed light on the NERICA project. The research and innovation at the basis of the NERICA project reflected essential parts of disruptive technology, infusing technological changes into crop research. Agricultural innovation through smart agriculture made it possible to monitor and manage anther culture and other embryo rescue techniques. The ability to monitor microscopic and physiological changes in a research environment provides opportunities to generate data that can be captured in real time, verifiable and valuable to inform research outcomes. The preceding elements informed the GeoFarmer design and implementation projects in East and West Africa as well as Latin America (Eitzinger et al. 2019). For example, GeoFarmer had real-time data capture capabilities, two-way data flows and involved farmers as co-innovators in the respective agricultural development projects. The measurement capabilities of the sensors in digital agriculture and the recognition of the knowledge base of farmers represent a fundamental shift in agricultural research processes, akin to Kuhn's (1970) idea of paradigm shift.

The increased adoption of NERICA was due to the methodological orientation of the project, a change from the system in agricultural research focused on technical questions and where research scientists, as experts, set and drove the research agenda. In such cases, farmers, as end-users of research did not play any role and were simply expected to trust the work of experts. Thus, when the agricultural research system, for example, did not contribute to agricultural development, it was because farmers "refused" to use new technologies. However, no attention was paid to the problems in setting the research agenda, the power play among the various actors in agricultural research, and the lack of representation of the farmers' viewpoint within the research system. These are issues researchers must address for farmers to embrace and integrate research findings into their production practices.

The NERICA project, however, moved away from the perennial issue of the participation of farmers as legitimate actors in agricultural research and integrated them as co-knowledge creators. Participation is premised on the assumption that groups partake in decisions that affect them (Brett 2003). Participation also engenders a sense of ownership and the subsequent acceptance of a specific policy. NERICA shows that when farmers are properly involved in agricultural research, there are positive outcomes. As rational actors, farmers are concerned about their food security needs and thus cautious in adopting any technology, especially in cases where they have no role in the agricultural research agenda in the first place.

The change in orientation in the NERICA project is consistent with an agricultural research that factors in both technical and non-technical or social considerations. These considerations are significant because they intersect at the farm level, where production takes place, the community, where support services for agricultural production are located, ►

► and at a societal level, where consumers make use of agricultural produce (Ruttan 1982). This approach therefore recognizes a close collaboration between technical and social aspects of research, what Biggs and Farrington (1991) call the social science analysis of agricultural research. Technical and social aspects of agricultural research, they argue, "are continuously and inextricably interwoven. To pull them apart leads to situations where policies and programs designed to achieve one set of objectives result in very different outcomes" (Biggs and Farrington 1991:3).

At stake is the fact that the social environment shapes research outcomes and vice versa. Explaining agricultural research outcomes should, therefore, begin with an understanding of the social and technical aspects of the process. Clearly, any analysis of agricultural research outcomes should go beyond technical concerns and focus on farmers' knowledge and their role in creating new forms of knowledge. Agricultural research in most African countries is basic research, and the scientific investigation that advances the frontiers of knowledge is minimal. At the same time, the bulk of research is adaptive, aiming at adjusting knowledge gained elsewhere to local conditions. NERICA proved that adaptive research can be useful only when social and local conditions are considered. Thus, a focus on the social conditions of farmers is critical in terms of the processes of adaptation that will be implemented for successful outcomes.

Conclusion

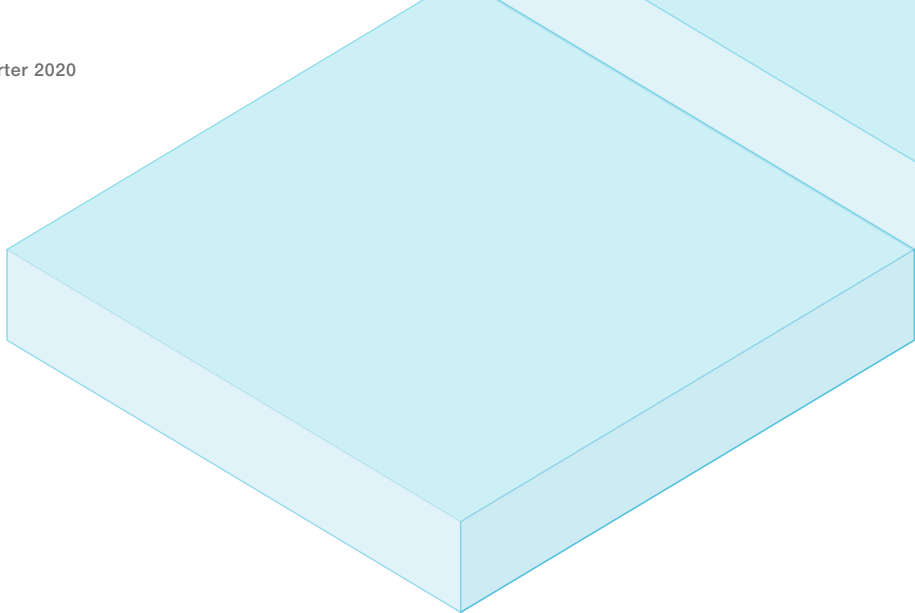
This article has shown the possibilities that technological changes can bring to agricultural development, and the interaction between technology and evaluation research. Specifically, the article focused on disruptive technology and its implications for evaluation research taking the case of NERICA as an example. Rice production benefited from research

and innovation as well as the integration of technical and non-technical issues into the research agenda. There are several valuable lessons for the future. First, disruptive technology and evaluation research must bear in mind the complex interaction between the producers and users of knowledge and recognize their common interests and goals. Traditional models of agricultural research neglected farmers' knowledge as a starting base of their research agenda, while evaluation researchers also focused on the technical at the expense of non-technical issues. Put differently, when it comes to evaluation research and agricultural research systems, the focus must be on both technical and non-technical factors, especially the location of farmers. This must be stressed because NERICA conclusively established that a concerted effort is needed to genuinely involve farmers in agricultural research institutions and policies, if the policy objective is to increase agricultural production and ultimately agricultural and national development in Africa.

Second, technology is not neutral in its impact. The focus on non-technical variables should be sensitive to, for example, the digital divide, which brings to the fore questions such as the access to and related cost of technology and the type of farmers. Two issues are at play. On the one hand, smart farming has undermined the historical split between large-scale and small-scale farmers in Africa, in which the former produced export agriculture and the latter produced for the local market (AGRA 2017). On the other hand, the rural-urban divide, a feature of many African societies, also reflects the location of the relevant infrastructure. Internet connectivity and bandwidth matters must be addressed for farmers, so that irrespective of their location, IoT and evaluation research can better contribute to the performance of African agricultural institutions and policies in our increasingly interconnected and wired 21st century society.

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Energy Digitalization and Impact Evaluation

Energy infrastructure is undergoing a paradigm shift towards a digitally enhanced, multi-dimensional and integrated system. This article investigates the implications of energy digitalization on impact evaluation via access to location- and time-specific data on electricity loads. Such large-scale and timely data will help evaluations reflect values created by new technologies and ultimately promote innovative financing instruments to enable energy market reform.

Yang Liu, Macroeconomics Policy, Forecasting & Research Department, AfDB.

Key Messages

- Energy digitalization is transforming the way electricity is supplied and consumed, blurring the distinction between supply and demand.
- Higher granularity of data can address heterogeneity in impact evaluation.
- Frontier impact evaluation enables market change and guides energy policy.

Introduction

The advent of information and communications technology over the last decade has had profound implications for how different elements of the power sector interact—specifically, two-way communication between utilities and customers, responsive transmission and distribution networks, and software and protocols allowing for interoperability among a multitude of actors and technologies (Liu and Zhong 2018). The implications of these digitalization trends on impact evaluation of energy infrastructure are profound. The greatest transformational potential of energy digitalization is its ability to blur the distinction between supply and demand, and to enable the interaction with consumers to balance demand with supply in real time (Liu et al. 2020).

This article addresses the issue of energy digitalization, and how it is transforming electricity supply and consumption, blurring the distinction between supply and demand. It also highlights how technology (e.g., smart grids, automated meters and block chain) offer tremendous opportunities for impact evaluators to make the most of location- and time-specific data on electricity loads which would otherwise not have been accessible.

More Data and Better Evaluation

The increasing connectivity, stemming from digitalization, generates a great amount of data, providing a robust and cost-effective tool for addressing heterogeneity in impact evaluation. The key success factor of impact evaluation is to conduct a counterfactual analysis, which is meant to disentangle the impact of a policy or program intervention and inherent attributes of individual units. It is well known that heterogeneity is a major issue on the applied grounds of impact evaluation. Considered observations are not identical and cannot be added to form an aggregate.

Household energy consumption behavior varies across different segments of the population. This heterogeneity may relate to household characteristics such as income, age, education and energy-saving awareness. For example, to better understand the impact of a subsidy program for energy-efficient household appliances, there is a need to disentangle the policy-driven and household-specific effects on the changes in energy consumption (Yao et al. 2014).

Today, energy digitalization significantly improves the accessibility of big data on load profiles and prices at specific times and ➤

► locations. The average cost of a smart meter has dropped by about one-quarter since 2008, with nearly 800 million smart meters being deployed globally as of 2017. The International Energy Agency (IEA) estimates that by 2040, 1 billion households and 11 billion smart appliances could actively participate in interconnected electricity systems across the world. Combined with the increased use of digital sensors and control equipment, these smart appliances can be connected to a network and controlled remotely (IEA 2019).

Disruptive technologies, such as block chain and machine learning, enable customers to track and identify clean energy sources, and thus conduct peer to peer trading of renewable electricity, which would have large implications on redefining the interaction of consumers with energy suppliers and electricity retailers. Such technologies can also significantly alter how people view and manage their energy services.

A data-enabled energy management system will certainly facilitate data-intensive evaluation of the impact induced by a policy or program intervention, not only in the way end-users can be more easily engaged as part of randomized control trials or field surveys, but more importantly in the sense that we can better control for heterogeneity of a large number of treatment groups through data analytics. Similarly, an automated energy metering system will enable matching large-scale heterogeneous attributes with policy changes in a cost-effective and timely manner; while a block chain-enabled energy monitoring system can greatly enhance transparency of an impact evaluation.

New Market and Frontier Evaluation

More than ever, as the energy market is undergoing a paradigm shift, impact evaluation practitioners today are expected to deepen their understanding

of innovative policy design and business models. Specifically, this calls for frontier insights into the effects of policy changes, through which new market players can deliver accessible and affordable energy goods and services to underserved communities.

In many African countries, ageing and overloaded transformers of central grids cannot keep up with peak demand. Consequently, load shedding and power outages are a major impediment to reliability of electricity supply. Meanwhile, Africa is the second largest and the fastest growing mobile market in the world. This disconnect is leading to a rethink of the energy sector. For instance, in Nigeria, Upnepa.ng¹ set up an Internet of Things (IoT) mobile platform to provide real time information on the total hours of electricity supply in local communities. The system detects the current state of power supply (On/Off), records the last time power was restored or disrupted, and predicts when next it might be restored or disrupted. Based on this information, households who own back-up power generators can host those who need power at an affordable rate. The business concept is like a kind of Airbnb, but for energy.

By connecting peers with each other, this collaborative economy business model can value the under-utilized and already existing assets. With this model, small energy developers gain a major benefit in terms of the cost structure. They can scale up their business extremely fast if potential customers are willing to join the collaborative network.

To grasp the impact of such systems, evaluation practitioners will need to sharpen their skills to undertake an impact assessment of these new developments. With the support of novel digital tools, it is easier today to integrate dispersed and small end-consumers and suppliers into a large-scale evaluation program. This enhanced representativeness ►►

► is particularly critical if impact evaluation is to play a key role in assessing the many benefits of these innovative business models (made possible by digitalization) at the broader societal level.

Currently, the global off-grid solar sector serves 420 million users, and accounts for a USD 1.75 billion annual market (ESMAP 2020). In Africa, Kenya, Tanzania and Ethiopia together account for around half of the 5 million people with access to new solar home systems in 2018 (IEA 2019). This notwithstanding, it is a known fact that to accelerate electrification in Africa, the most expensive to reach often also happen to be the least able to pay and/or consume when connected.

Most of large-scale electrification program interventions will not be economically viable unless markets are able to translate wider social and economic impacts into business values. Obviously, these electrification projects have good potential to expand to other critical social services such as solar water pumps, cold storage, support to community healthcare and schools. However, it is imperative that multiple impacts are explicitly monitored, evaluated and reported. Doing so will help to demonstrate some of the pay-for-success

instruments such as social impact bonds and development impact bonds—innovative financing mechanisms that make funding conditional upon the delivery of concrete results, and most importantly, directly reward high impact firms with premium payments for achieving social results.

Conclusion

Energy digitalization is transforming the way the electricity is supplied and consumed, blurring the distinction between supply and demand. Deployment of smart grids, notably automated meters and block chain technologies will offer tremendous opportunities for impact evaluators to make the most of location- and time-specific data on electricity loads which would not have been accessible otherwise. Digital tools will also enable a cost-effective and timely evaluation program by incorporating massively dispersed observations, while the pace of decentralized trends is accelerating for the future energy infrastructure landscape. More importantly, this much needed evaluation work will capture system-wide costs and benefits and thus help unlock the full potential of innovative business models in the energy market.

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Endnotes

1. Upnepsa.ng is an IOT-powered platform which gives real time information and history of electricity supply in selected communities and homes across Nigeria. For more, visit: <https://upnepsa.ng/>

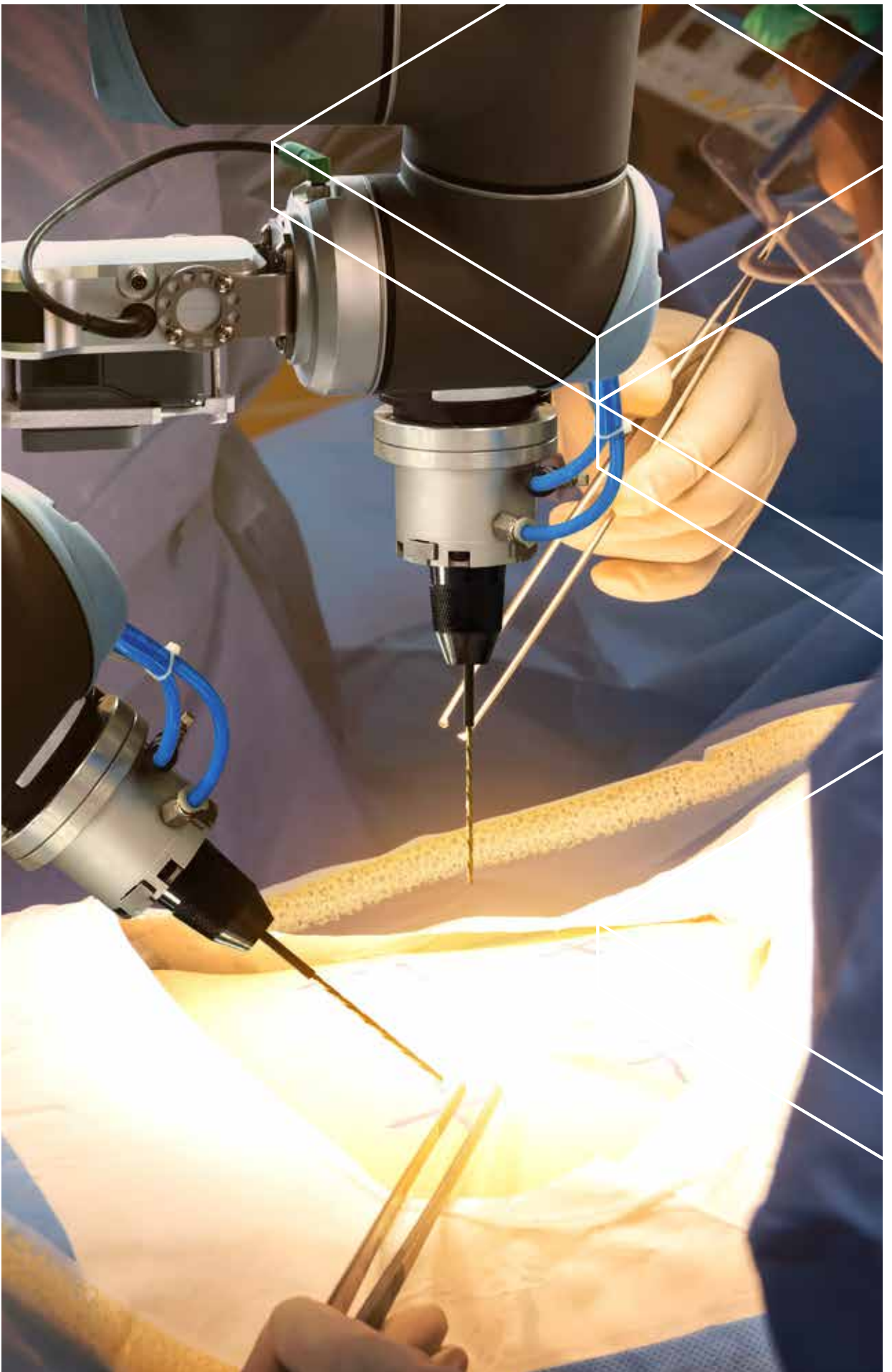
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Application of SurveyCTO mobile data collection technology in household surveys: The case of an impact evaluation of the Community Based Integrated Water Resource Management Project in Niger

Interest in enhanced data quality at reduced cost continues to grow globally. While evaluators previously relied on paper-based surveys, with the attendant challenges of poor data quality and increased cost and time of data collection and entry, there is a shift toward the use of digital surveying. While many tools with varying mobile data collection functionality exist, finding the most suitable one, mindful of data security, cost, ability to work offline and ease of use, is key. One such software is SurveyCTO – a product that gathers high-quality data using Android phones/tablets, or via the web. This article examines the use of SurveyCTO for data collection in an impact evaluation of a community based integrated water resource management project in Niger. It highlights the pros and cons of SurveyCTO in comparison to a paper-based survey. It also highlights how SurveyCTO can find application in development organizations and contexts including that of the AfDB.

Andrew Anguko, Independent Development Evaluation, AfDB.

Key Messages

- SurveyCTO is a reliable, secure, and scalable mobile data collection platform for researchers and professionals working in offline settings.
- Use of SurveyCTO reduces the cost and time of data collection and increases the quality of data.
- SurveyCTO allows data collection teams to disseminate preliminary findings to stakeholders immediately after data collection is completed.

Introduction

In conducting household or individual surveys for evaluations, the traditional approach has involved using paper questionnaires filled in manually by enumerators during interviews. Then each evening, survey supervisors and coordinators check the quality and consistency of the responses reported in the questionnaires. Once all the interviews are conducted, and fieldwork is concluded, data-entry clerks transcribe the information from the paper questionnaires into a digital format. This process, however, is problematic (Lombardini et al. 2018). First, the **quality of the data**—there are several opportunities for the introduction of errors during the data-collection and data-entry processes; and second, the **time lag between the data collection and when the data is ready for analysis** can prevent or significantly delay the feedback to communities and utility of the data.

Minimizing errors is critical in the case of impact evaluations with a limited sample size. As Caeyers et al. (2012) suggest, errors tend not to be randomly distributed across a sample, but are correlated with household characteristics, which can potentially introduce bias in analysis if observations need to be dropped. Using

digital data collection methods can mitigate some of the problems inherent in the use of paper-based surveys. This is particularly key where data collection involves household surveys that assess the performance of development interventions. This was the case with the impact evaluation of the community based integrated water resource management (CBIWRM) project where SurveyCTO¹ was utilized. The intervention was implemented by Oxfam in Banibangou and Soumatt communities of Niger, jointly with Karkara, a local partner, and the Department of Agriculture, Niger.

The CBIWRM Project

The project, which commenced in April 2013, was completed in March 2015, and evaluated a year after closure. Central to the project's overall objective was a focus on increasing agricultural production and farmers' income – particularly women. Crops targeted for enhanced production included cabbages, tomatoes, onions, carrots, potatoes and sweet peppers. The choice of these crops was based on specific problems experienced by farmers in the two villages—very low levels of rainfall, local farmers' low capacity to produce crops, and a lack of necessary inputs. ➤

► Karkara played a vital role in addressing these issues – notably by developing irrigation systems. With funding from Oxfam, wells and boreholes were dug, while water tanks with solar pumps were installed. Pipelines were linked to water basins in order to improve irrigation in the community, and farmers were given seeds and agricultural tools to boost crop production. Karkara then partnered with the Department of Agriculture to train farmers on improved agronomic practices, organized field exchange visits, and encouraged farmers to establish groups to enhance their bargaining power at local markets. Oxfam funded the project’s implementation and coordinated project activities, routinely monitoring activities via site visits to ensure smooth implementation (Oxfam 2019).

The Survey and Sampling Design: The primary goal of the project evaluation was to determine the impact of the intervention on beneficiaries’ household income. Evaluators used a quasi-experimental impact evaluation design, which involved comparing households that had been supported by the project with households in neighboring communities that had not been supported, but who had similar livelihood characteristics prior to the project being implemented. The evaluation covered four villages (two project and two control villages). Households involved in the project were randomly selected

and interviewed. For control purposes, interviews were carried out with households from two villages that had not participated in the project, but who had been eligible and had expressed an interest in doing so. The control villages were selected purposively because they were deemed to have had similar characteristics to the implementation villages at baseline (prior to onset of project). In total, 300 project participants and 404 non-participants were interviewed.

Statistical tools of propensity score matching (PSM) and multivariate regression were used to control for demographic and baseline differences between the households in the project and control villages, in order to increase statistical confidence when making estimates of the project’s impact (see Caliendo & Kopeinig 2008). Table 1 below lists the villages and the number of households/farmers interviewed in the intervention and control villages.

SurveyCTO Software and its features: The evaluation team selected the SurveyCTO software for several reasons. Firstly, a unique feature of this software is its ability to use many languages, including non-Latin characters. Also, the tool can be used entirely offline, from building the survey to data analysis – making it ideal for areas with limited connectivity such as Niger. Third, the tool has an advanced ►

Table 1: Intervention and control group sample sizes

	Project participants			Sample comparison group		
Commune	Villages/ farmer associations randomly selected from intervention communities	Households/ farmers participating in the project	Households/ farmers interviewed	Commune	Villages/farmer associations selected in comparison communities	Households/ farmers interviewed in comparison communities
Banibangou	Banibangou	320	147	Banibangou	Garbey	200
	Soumatt	392	153		Gossou	204
Total		712	300			404

► design functionality to accommodate the structure of long and complex survey questionnaires and an inbuilt functionality to run frequencies when the survey is completed. This enables fast feedback to the community surveyed. Finally, its robust encryption features make it invaluable to data collectors for whom data security is paramount. There are eight keys prerequisite steps to using SurveyCTO², with guidelines and standardized tools to support the process (Tomkys et al. 2015).

Potential Applicability in Evaluations and Associated Benefits

This section highlights how the application of SurveyCTO and other digital platforms can contribute to enhance evaluation within the African evaluation community, including the AfDB. The analysis focuses on five broad areas: a) cost, quality and time of data collection; b) data security; c) ethics; d) community/client engagement; and e) versatility of use. To ensure balance, the section also highlights potential challenges of SurveyCTO and similar tech platforms.

■ **Cost, quality and time of data collection:** The average cost of a paper-based questionnaire in data collection is estimated to be almost 1.5 times more as compared to employing SurveyCTO. In the Niger study, data collection took 8 days as compared to 2 weeks for a paper-based survey of the same sample size. Also, the SurveyCTO data quality was better due to inbuilt checks and the ability of the survey team to provide immediate feedback to the community. Further, SurveyCTO has the potential to improve data quality by monitoring incoming data in real time while data collection is still underway. This allows for a quick identification of survey flaws; enumerators who need additional supervision; and data

errors and discrepancies that need correcting. For African evaluators, this tools will be beneficial in household surveys, particularly for impact evaluations, where sample sizes are key. The cost reduction realized by using SurveyCTO can translate into more evaluations being done and more evaluative knowledge being generated.

■ **Data security:** Concerns over data privacy and cybersecurity have led to growing trends of in-country or on-premise data hosting³. Data privacy and cybersecurity concerns continue to grow, exacerbated by the occurrence of large-scale data breaches, such as the Capital One data breach that compromised the private data of over 100 million consumers (FBI 2019). SurveyCTO approaches the challenge of web vulnerability by providing its users the highest levels of data security through end-to-end encryption. End users generate and fully control a public-private key pair used for encrypting and decrypting data. In this way, if one's data is stolen or otherwise breached, it remains safe provided the encryption key is not also stolen or compromised. This feature can be utilized by evaluators especially in evaluations of non-sovereign or private sector operations, where utmost confidentiality of data is required.

■ **Principle of respect and ethics:** Consent is an ethical and legal requirement in evaluation. To this end, all evaluations should be designed and executed in compliance with the rights, values and physical integrity of stakeholders and their communities. Evaluators should respect the dignity and the human values of all persons/groups involved in the evaluation such that no one feels coerced, threatened, or harmed physio-culturally, or due to their ►

► religious belief. Evaluation findings should also be owned by stakeholders and the limits of the methodologies employed should be precise. Privacy should be maintained during the evaluation process to minimize any undue influences on evaluators—hence why consent should always be sought prior to the onset of an interview. A unique feature of SurveyCTO is its ability to be programmed such that it prevents enumerators from proceeding with an interview unless the consent field is signed. This ‘trigger’ ensures that ethical guidelines are strictly observed.

■ **Increased community engagement through timely feedback:** Ethics dictate that when respondents dedicate time to participate in household surveys, to close this loop, evaluators in turn need to share the results/findings with the individuals who provided the data. This is not standard practice and where it does happen, it is often done well after the survey. Using technology to gather data enables the processing of survey data in real time. This facilitates the sharing of survey data with communities almost immediately, even while fieldwork is still ongoing, and has the potential to increase engagement and participation with surveyed communities. Again, it aids knowledge-sharing and the prioritization of community needs.

■ **Survey in multilingual setting:** SurveyCTO allows for the crafting of surveys in multiple languages, including question text, answer options, hints, and even any media, such as images, audio clips, and video clips. There’s no limit to the number of languages that can be programmed, and respondents can switch between languages as needed. This feature has promise for international institutions such as the AfDB, which conduct evaluations in multi-lingual and

complex ethno-cultural settings, but also for evaluators who survey participants in local languages. This flexibility to design language specific and culturally nuanced surveys can boost participation and increase the validity and reliability of responses.

Challenges with SurveyCTO

Like all things technology, glitches can prevent or disrupt the quality and feasibility of the data-collection process using SurveyCTO. First, the challenge with varying levels of technological literacy. If enumerators are not familiar with use of mobile devices/tablets, this can impact the quality of data gathered. Second, weather conditions (e.g., dust and moisture) can also adversely impact the functioning of devices.

In the case of Niger, the project negotiated these challenges by training enumerators to properly navigate the devices. Guidelines and troubleshooting tips to aid the enumerators and supervisors were also provided. Regarding the weather, zip lock bags were utilized to minimize dust and rain damage. However, the temperatures in Niger made the devices hot and uncomfortable to hold for long periods. Another challenge faced was the theft of devices. This, if not addressed, can result in valuable data losses, and delays as enumerators are compelled to re-survey respondents.

Conclusion

The impact evaluation in Niger shows how ICT and particularly SurveyCTO can add value and play a key role in an evaluation. There were considerable improvements gained in data security, accountability, accuracy, timing and cost. Where technology is readily available, organizations should use digital surveys if feasible. Platforms such as SurveyCTO allow various evaluators to streamline, ►►

► organize and assess their field data collection in real time. Evaluators can seamlessly submit their forms remotely for an immediate review/fact-checking, thus enhancing productivity and minimizing turnaround time. This positively impacts the validity of the study, and reduces the time and resources spent on data cleaning, which can instead be channeled to tasks such as feeding results back to the communities. SurveyCTO also offers robust dashboards and automated

reports, further enhancing confidentiality, data security, and efficiency. Surveys can be completed offline, with data being auto-sent once connectivity is restored, minimizing field stress associated with working in remote areas or with limited connectivity.

For African evaluators, such a tool holds much promise especially considering the restrictions that have been imposed on many due to the COVID-19 pandemic.

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Endnotes

1. SurveyCTO, is a software that gathers high-quality data via Android phones/tablets, or the web, by way of personal interviews (i.e., Computer Assisted Personal Interviews) or phone (Computer Assisted Telephone Interviews (CATI)).
2. For more on the eight steps, see Tomkys et al. (2015).
3. The data security landscape changed dramatically with the adoption of the General Data Protection Regulation (GDPR) in 2018, which introduced strict standards for processing sensitive personal data and steep fines for violators.

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Morocco to host sixth APNODE Annual General Meeting

The sixth Annual General Meeting (AGM) of the African Parliamentarians' Network on Development Evaluation (APNODE) will take place in Rabat, Morocco, hosted by the Kingdom's House of Councilors. Originally foreseen for July 2020, the AGM had to be rescheduled due to the travel restrictions related to the COVID-19 pandemic. The new date will be announced in due course.

Guided by the theme *Enhancing Parliamentary Oversight for Transformative Development*, the AGM will, among others, reflect on the first 5 years of APNODE to forge ahead for the next five. The forum will also hold two high level panel discussions on: a) *Enhancing Parliamentary Oversight for Transformative Development – What are the Strategic Imperatives?* and b) *10 years to achieve the*

Sustainable Development Goals: How can African Parliamentarians Catalyze Progress?

The AGM is expected to attract Speakers of the House/ Senate, Members of National Assemblies and Senators from across Africa, as well as representatives from development partners and centres of expertise such as AfDB, UNDP, UNICEF, UN-Women, EvalPartners, CLEAR (Centers for Learning on Evaluation and Results), Global Parliamentarians' Forum on Evaluation (GPFE), and RFE (*Réseau Francophone de l'Evaluation*). Also expected are representatives from Africa's regional parliaments.

Find out more:

● <http://idev.afdb.org/en/news/morocco-host-sixth-apnode-annual-general-meeting>



IDEV publishes its 2019 Annual Report

For IDEV, 2019 was a year of helping the Bank and its Regional Member Countries to transform experience into knowledge and learning through independent evaluations, and supporting them to achieve their development goals through the lens of the AfDB's High 5 Priorities, the 2030 Agenda for Sustainable Development, and the African Union Agenda 2063. IDEV delivered 13 evaluation products, conducting and facilitating evaluations, knowledge sharing events, and capacity development activities in more than 26 countries in Africa.

IDEV's evaluations informed high-level discussions and decisions, such as those on the Bank's 7th General Capital Increase and the 15th replenishment of the African Development Fund. It also introduced new evaluation products that responded to the Board of Directors' and Bank Management's expressed knowledge needs, and its evaluations contributed to the continuous improvement by the Bank

of its systems, processes and mechanisms for delivering on its mandate.

The report is available in French and English and is presented in more detail on a dedicated webpage:

● idev.afdb.org/en/AR2019

Find out more:

● <http://idev.afdb.org/en/news/idev-publishes-its-2019-annual-report>



African parliamentarians share their experience of tracking progress on the UN Sustainable Development Goals as part of gLOCAL Evaluation Week

As part of its contribution to the [gLOCAL Evaluation Week](#) that took place from 1 to 5 June 2020, IDEV facilitated a [webinar](#) co-organized by the African Parliamentarians' Network on Development Evaluation ([APNODE](#)) and the Centre for Learning on Evaluation and Results-Anglophone Africa ([CLEAR-AA](#)). The webinar, which was held on 5 June 2020, aimed to share parliaments' experiences in i) identifying national SDG priorities, ii) providing guidance on their implementation to ensure that national actions reflect and address specific national needs and circumstances, and iii) monitoring and tracking national progress towards the SDGs.

Over 50 participants from across Africa and beyond attended the webinar which was co-moderated by Mr. Kobena Hanson from IDEV and Ms. Hermine Engel from CLEAR-AA.

Hon. Evelyn Naomi Mpagi-Kaabule, former Member of Parliament from Uganda and APNODE Chairperson, and Hon. Stanley Kakubo, member of the National Assembly of Zambia and Interim Chairman of the Zambian APNODE National Chapter, served as panelists and shared their experience in implementing and tracking progress towards the SDGs. In their talk, they

explored success factors and good practices for tracking SDG progress such as structures, partnerships and explicit actions put in place to facilitate this.

Find out more:

● <https://idev.afdb.org/en/news/african-parliamentarians-share-their-experience-tracking-progress-un-sustainable-development>



IDEV webinars

Rapid Evaluation

This webinar held on 3 June 2020 presented an introduction to rapid evaluations, their general purpose amongst other evaluation approaches, and their approach and methodology. The benefits and limitations and the general value offering of rapid evaluations were also presented. Several concrete examples were used to illustrate the approach: a rapid assessment of the

readiness of State-Owned Enterprises in South Africa to take on board the evaluation function and their inclusion in the national evaluation system, as well as a rapid evaluation of the DPME evaluation training courses delivered in 2012-2018 to national and provincial departments and Offices of the Premiers.

Find out more:

● <http://idev.afdb.org/en/document/webinar-rapid-evaluation>

planning, monitoring & evaluation
Department: Planning, Monitoring and Evaluation
REPUBLIC OF SOUTH AFRICA

Rapid Evaluations Toolkit

Antonio Hercules
April 2019

CONTENTS

- 1. Introduction
- 2. Rapid evaluation Design
- 3. Outputs
- 4. References and further reading

Evaluation of AfDB Support to the Water Sector, 2005-2016 Beyond infrastructure development: Toward service delivery and behavioral change

This report summarizes the findings, lessons and recommendations from an independent evaluation of the support provided by the African Development Bank Group to the water sector from 2005 to 2016. This includes support for Water Supply and Sanitation in both the urban and rural context (UA 3.7 billion over the evaluation period) and for Agricultural Water Management (UA 2.2 billion). The evaluation aims to inform the Bank's strategies and operational approach to water sector assistance by examining the extent to which the Bank has contributed to the development of the water sector in African countries and

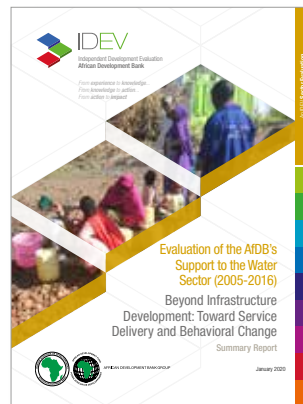
Reaching the Most Vulnerable: Scaling up Service Delivery in Urban Water Supply and Sanitation

This report summarizes the results of a cluster evaluation of 15 AfDB-funded Urban Water Supply and Sanitation (UWSS) projects that were implemented in 12 African countries over 2001-2016, with a value of UA 342 million. The evaluation assessed the performance (relevance, effectiveness, efficiency and sustainability) of the selected projects and drew lessons for the design and implementation of future UWSS projects in line with the Bank's High 5s priorities related

by identifying lessons on how the Bank can contribute most effectively to improving the performance of the sector.

Find out more:

🔗 <https://idev.afdb.org/en/document/evaluation-afdb%E2%80%99s-support-water-sector-2005-2016-beyond-infrastructure-development-toward>



to improving the quality of life for the people of Africa.

Find out more:

🔗 <https://idev.afdb.org/en/document/reaching-most-vulnerable-scaling-service-delivery-urban-water-supply-and-sanitation>



Towards a Service Delivery Approach to Rural Water Supply and Sanitation

This report synthesizes the results of a cluster evaluation of 16 AfDB-funded Rural Water Supply and Sanitation (RWSS) projects that were implemented in 13 African countries over the period 2000-2017, for an amount of UA 365 million. The evaluation assessed the performance of the projects and drew pertinent lessons for the policy and practice of designing and implementing future RWSS projects. It examined the relevance, effectiveness, efficiency and sustainability of the projects, the extent to which the intended project results were achieved, and the factors that facilitated or limited their achievement.

Find out more:

🌐 <https://idev.afdb.org/en/document/towards-service-delivery-approach-rural-water-supply-and-sanitation>



Strengthening Agricultural Water Management to Feed Africa

This report summarizes the results of a cluster evaluation of nine AfDB-funded Agricultural Water Management (AWM) projects in seven African countries that were implemented between 2005 and 2016, with a total value of UA 150 million. It aims to inform the design and implementation of the Bank's future AWM interventions in the context of its *Feed Africa* Strategy. The evaluation assesses the results of the projects (examining relevance, effectiveness, efficiency and sustainability) and distills lessons which the Bank and its stakeholders, including governments, civil society and development agencies, can use in future AWM interventions.

Find out more:

🌐 <https://idev.afdb.org/en/document/strengthening-agricultural-water-management-feed-africa>

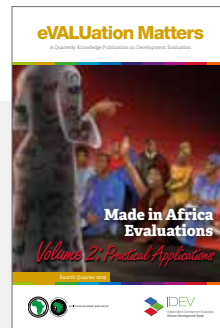




First Quarter 2020: *Promoting an Evaluation Culture in 2020 and Beyond*

This edition examines new thinking and strategies around promoting a culture of evaluation. Contributors, individually and collectively, address the Why, What, and How issues by interrogating questions such as: Why do we need an evaluation culture? What should an evaluation culture look like? How to achieve an evaluation culture? Which processes, policies and tools are needed?

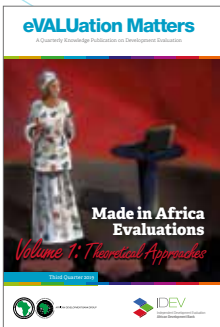
<http://idev.afdb.org/en/document/promoting-evaluation-culture-2020-and-beyond>



Fourth Quarter 2019: *Made in Africa Evaluations Volume 2: Practical Applications*

This edition and second volume on 'Made in Africa Evaluations (MAE)', explores practical indigenous evaluation applications and how they can fast-track the achievement of the continental development compacts – the UN Agenda 2030 and its SDGs and the African Union Commission's Agenda 2063. Contributors also explore the application of the MAE concept and what MAE evaluations should look like in practice.

<http://idev.afdb.org/en/document/made-africa-evaluations-volume-2-practical-applications>



Third Quarter 2019: *Made in Africa Evaluations Volume 1: Theoretical Approaches*

This edition addresses theoretical approaches toward a 'Made in Africa Evaluation', reviewing indigenous tools and techniques and how they can advance the achievement of Africa's development agenda. Contributors address key questions such as: What is meant by 'Made in Africa evaluation' and how does it differ from other approaches? What unique insights can an African cognitive lens bring to evaluation? How should countries go about creating indigenous evaluation practices?

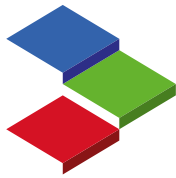
<http://idev.afdb.org/en/document/made-africa-evaluations-volume-1-theoretical-approaches>

Second Quarter 2019 : *Best practices and innovation in evaluation*

The edition examines best practices and innovations for a stronger evaluation culture. Contributors share their experiences in applying innovative techniques in the evaluation of rural development projects, innovative approaches for evaluating the impacts of environmental interventions, improved methods for examining sustainability, process tracing and the Most Significant Change technique.



<http://idev.afdb.org/en/document/best-practices-and-innovation-evaluation>



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