# Data collection and analysis tools for food security and nutrition

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## INTRODUCTION

### *"Food systems have failed us"*

Back in 2019, when José Graziano da Silva made his last intervention as Director General of the United Nations' Food and Agriculture Organization (FAO) and when, later, the UN Secretary General Antonio Guterres announced the convening of the first World Food System Summit, they both made a very bold statement, which has since been extensively quoted: "**food systems have failed us**".

Even before COVID-19 made its unsettling appearance, lack of sufficient progress towards Targets 2.1 and 2.2 of the Sustainable Development Goals (SDG) had made it clear that **existing food systems worldwide are unable to guarantee food security and adequate nutrition for all** and that **a significant transformation** is needed to hope to bring things on track. What is less clear, is *why* current food systems are not up to the ambitions that inspired the formulation of the Sustainable Development Goal (SDG) number 2, and in particular of Targets 2.1 and 2.2[1], and what kind of transformations are likely to be more effective in achieving the desired outcomes.

Seen from the perspective of data and information – the focus of this report – having reached a conclusion regarding the "failure" of food systems implies that **existing data and information systems** are, at least, perceived to be sufficient to **reveal the scope of such overall failure**, as there is enough evidence of widespread malnutrition in its various forms. However, it also implies that data and information might be part of the problem, in the sense that, despite the incredible amount of data and information available nowadays, **these are not sufficiently timely, accurate or relevant, or are not properly analysed and used to guide** the actions of all agents involved in the management and functioning of food systems', including but not limited to public policy makers.

This report aims at contributing to the debate by exploring and discussing possible reasons why existing data and analysis tools for agriculture, food security and nutrition[2] may indeed be part of the problem, but also how they may be turned into **key elements of any proposed solution** to make food systems more sustainable and conducive to improving widespread health and nutrition outcomes.

### The context

During its 46th Plenary Session (14-18 October 2019), the Committee on World Food Security (CFS) adopted its four-year Programme of Work (MYPoW 2020-2023), which includes a request to the High-Level Panel of Experts on Food Security and Nutrition (CFS-HLPE) to produce a report on "Data collection and analysis tools" for food security and nutrition, to be presented at the 50th Plenary session of the CFS in October 2022.

The CFS requested that the report will:

- Identify the barriers impeding quality data collection, analysis, and use in decision-making.
- Identify specific high priority gaps in data production and analysis not covered by ongoing initiatives.
- Highlight the benefits of using data and the opportunity costs of not using data for decisions.
- Illustrate initiatives that have encouraged evidence-based decisions in agriculture and food security across the public, private, and academic sectors as well as approaches that have not worked.

[1] SDG Target 2.1 reads "By 2030, eradicate hunger, ensure food security

[2] See the glossary for definitions of the terms used in the report.

- Provide insights into how to ensure data collection and its utilization give voice to the people most affected by policies stemming from that data, including farmers and other food producers.

The report is produced in continuity with past HLPE reports that have explored the global food security and nutrition problem from various perspectives. In particular, the most recent conceptualization of food security as comprising six dimensions (availability, access, utilization, stability, agency, and sustainability) (HLPE, 2020; Clapp *et al.*, 2021) is used as an overarching reference to discuss the specific data and information-processing issues highlighted throughout and to guide the choice of potentially useful solutions.

## The scope

Comprehensive data for FSN must consider food production through to nutrition outcomes. Yet this implies data from varying sources, often guided by different conceptual frameworks, and varying priorities and points of entry into relevant issues. To have a clear picture and a reasoned discussion on current issues and to identify roles, responsibilities, as well as existing challenges and opportunities in the use of evidence to address extant food and nutrition problems, we will start in **Chapter1** by presenting a consolidated conceptual framework that guides this report, bringing together food systems, food security, and nutrition, identifying the points where relevant data enter in the picture and linking it to existing information systems. Without a clear conceptual framework as a reference, it is impossible to even discuss the merits and drawbacks of specific data, indicators, and analysis tools, and therefore it would be strange if we don't make it explicit, from the outset, which one guides our own discussion.

We also present a second analytic tool, which is a representation of the sequence of steps involved in an ideal data-cycle, from designing a data collection initiative, all the way to using the information to guide action, and where the cycle is closed by the various feedback channels originating at any step that aim to improve the next cycle of data collection.

**Chapter 2** will present a review of existing agriculture, food and nutrition data collection initiatives highlighting their primary area of focus (drawing on the report's conceptual framework), and primary intended purpose (from the phase in the report's data cycle). This chapter will also provide a brief overview of the challenges and barriers to data-informed policymaking for FSN, and identify examples of existing tools, advisory groups, and other efforts designed to address them.

As any other human-driven process, effective FSN information systems encompassing all functions included in the data cycle, from generation to use, will require effective governance at each step, an issue that will be tackled after having discussed, in **Chapter 3**, the extent of current constraints in terms of insufficient resources and capacity. Among them, the lack of sufficiently sophisticated analytic capacity seems particularly evident and relevant in the context of food security and nutrition assessment and will receive a dedicated attention.

While the review in Chapter 2 will focus on existing initiatives, we recognize that we live in a rapidly changing informational landscape. Therefore, **Chapter 4** will discuss the most important recent developments in terms of new and emerging data driven technologies that are potentially relevant for agriculture, food security and nutrition, and that may be useful to address some of the existing constraints. We expect these new technologies to soon become an integral part of the food and nutrition data cycle in the near future, and we shall discuss potential opportunities and risks.

With all the previous elements at hands, **Chapter 5** will focus on issues of governance. A recurring theme in discussions on the design of an appropriate data and information governance system, is the delicate balance to be found between the roles that the various agents holding a stake in the food and nutrition economy, in particular between what can be left to the unfettered private initiative, and what requires an active role by public institutions, at local, national and global levels.

The ambition is to provide useful recommendations on how food and nutrition information systems might be designed, implemented, and governed, from the local to the global dimension, to maximize their contribution towards the shared goal of eradicating food insecurity and provide better nutrition for all.

# 1. SETTING THE STAGE: A CONCEPTUAL FRAMEWORK TO INFORM DATA COLLECTION AND ANALYSIS TOOLS FOR FOOD SECURITY AND NUTRITION

The High Level Panel of Experts (HLPE) report nr. 15, entitled "Food security and nutrition. Building a global narrative towards 2030" (HLPE, 2020) concluded – among other things, that "The concept of food security has evolved to recognize the centrality of agency and sustainability, along with the four other dimensions of availability, access, utilization and stability. These six dimensions of food security are reinforced in conceptual and legal understandings of the right to food."

All six dimensions can be recognized by exploring food security and nutrition through their linkages to agriculture, health and environment systems, in a manner that is not entirely captured by the well-accepted, existing conceptual frameworks for food systems (HLPE, 2020), food security (ref.) and nutrition (ref.). This chapter presents a narrative that illustrates why these three conceptual frameworks must be brought together in a coherent whole and how they can be used to inform data collection and analysis tools for food security and nutrition.

Leveraging on elements in each of the inspiring frameworks, this report takes a **systems perspective**, recognizing the linkages between the various elements that form what might be termed the food security and nutrition socio-ecosystem. Drawing from socio-ecological models (Bronfenbrenner, 1979), in fact, it is important to consider that the elements that encompass FSN operate at different, but interrelated levels in a society: from the more distal, macro-level, to the immediate, individual person level, which is where the ultimate impact in terms of improved nutrition materializes.

It is also important to recognize that the boundaries between these levels (distal, proximate, and immediate), are somehow blurred. Elements of macro-level drivers, such as, for example, those related to climate, the environment, and the natural resource basis of a country, permeate into more proximal levels, represented by local agriculture and food, health, and environment systems, influencing them in different ways and with different intensity. These proximal systems are fundamentally shaped mainly by national policies (including by investments in logistics and infrastructures), that are still beyond the direct, immediate control of the individuals. In most societies today, the way in which citizens interface with the local food, health, and environment systems – and thus contribute to determine their ultimate food security and nutrition outcomes – is through personal, household and community-level decision-making and actions, all of which are also conditioned by the data and information people have access to.

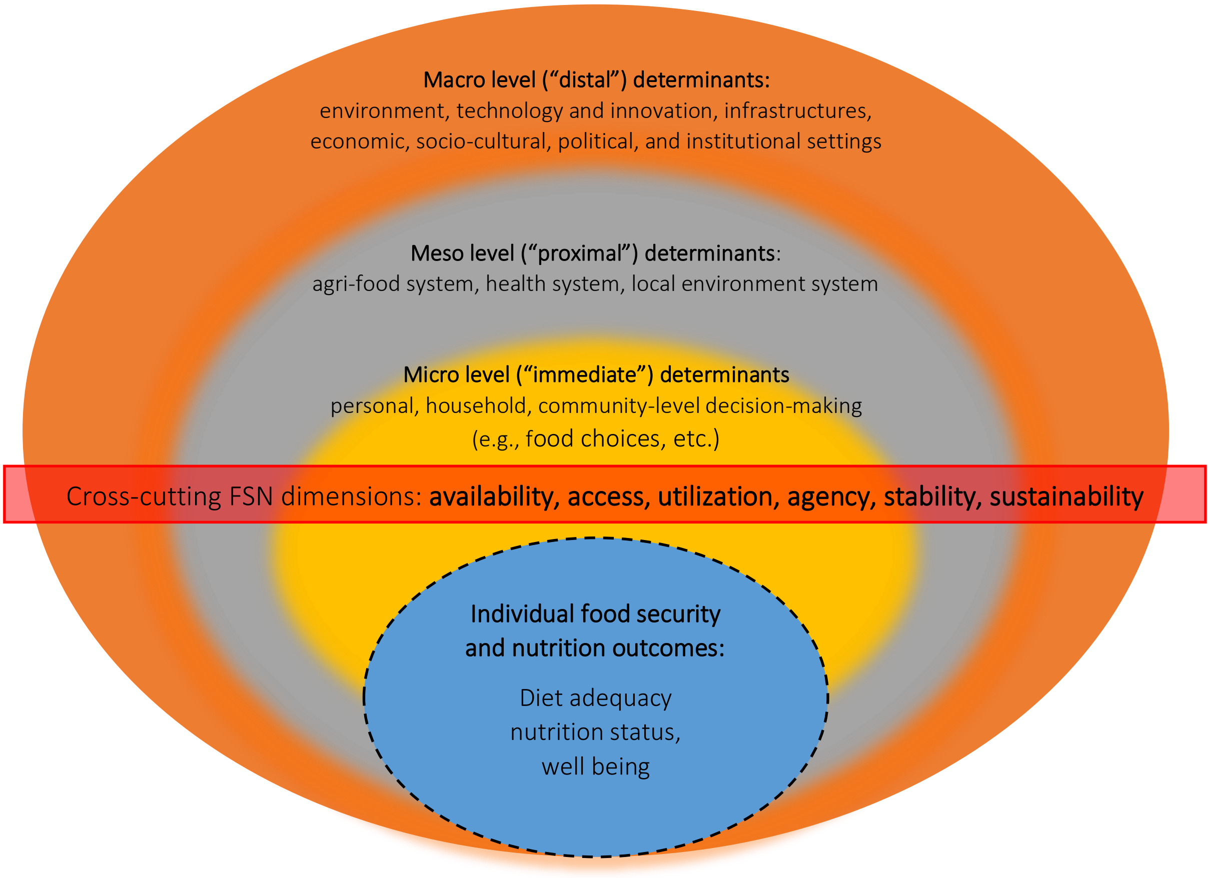
The drivers of food security and nutrition encompass macro-level constructs made up of many more fundamental elements that can be grouped into the following categories: environment; technology and innovation; infrastructure; economic; political and institutional; socio-cultural; and population demographics. (HLPE, 2020). Taken together, macro-level drivers contribute to shape the more proximal food, health and environment systems which jointly determine the enabling environment – made of availability, affordability, proximity, knowledge and practices related to food – for people to become agents of their nutrition. (HLPE, 2020, Figure 1) (UNICEF, 1990, Figure II).

For individuals to benefit from the flow of goods and services generated by the local food, health and environment systems, decision-making must take place individually or in coordination with their families or communities. It is at this interface between the individuals and the food and health systems and local environments where they live that people's food security and nutrition is determined.

The diagram in Figure 1 is intended to illustrate how the boundaries between macro-, meso-, and micro- level determinants are somehow blurred and how all of them permeate up to the individual level, to jointly contribute to determine short-, medium- and long-term food security and nutrition outcomes, such as dietary adequacy, individual nutritional status and overall well-being.

Finally, cross-cutting the four inter-related levels of our conceptual framework for FSN are the 6 dimensions of FSN: agency, stability, sustainability, access, availability and utilization (HLPE, 2020)

Figure 1 Conceptual framework for a systemic view of FSN determinants and outcomes




*Source: the authors. Adapted from concepts included in the HLPE food systems framework, UNICEF's conceptual framework of nutrition, and socio-ecological models (in the tradition of Bronfenbrenner, 1979)*

In addition to the fundamental constructs and their relationships as illustrated in the conceptual framework in Figure 1, another critical conceptualization involves recognizing the steps needed to ensure effective and efficient data-driven decision making.

To this aim, we have adapted the data value chain from the Nutrition Data for Accountability and Action Framework (Piwoz *et al.*, 2019) to illustrate 4 critical stages in the process of data driven decision making cycle for food security and nutrition below.

## Figure 2 Data driven decision making cycle for FSN


*Source: the authors. Based on the Data Value Chain and adapted from (Piwoz* et al.*, 2019)*

Our data driven decision making cycle consist of the following four steps:

1. Priority setting: Define evidence priorities and questions
2. Data: Review, consolidate, collect, curate, and analyse data
3. Translation: Translate and disseminate results and conclusions
4. Utilization: Engage and use results and conclusions to make decisions

### 1.1. Using the conceptual framework and data drive decision-making cycle to address issues relevant for FSN

Prior to any data collection, it is important to clearly define a set of one to three evidence priorities that motivate the task at hand and identify focused questions with clear linkages to said evidence priorities. The one to three evidence priorities, and related questions, will be used as a strict guide for the subsequent steps in the data driven decision making cycle.

Once priorities are clear, the next step in this cycle is to review and consolidate any existing data on the topic. In many cases, it may turn out not necessary to collect new data and it may suffice to soundly organize the existing data in way that it is useful to answer the questions.

Once the existing data is organized, and if the questions are still not satisfactorily answered, it is possible to plan the collection of new data. To ensure both effective translation and utilization, it is extremely important to plan any new data collection in relation to both the evidence priorities and conceptual framework for FSN. We have designed a matrix in which both the conceptual framework and data driven decision-making cycle are used to address the issues relevant for FSN; with a particular aim of parsing the new data collection that would be necessary for such work. This matrix will be explained with complementary examples later in this section.

Once new data is collected, it must be entered into a data management platform and analyzed in a sensible fashion. The next step in the data driven decision making cycle is to construct the necessary outputs for said data driven decision making. Specifically, the analytical results should be summarized (i.e., translated) in ways that facilitate ~~the reading of both clear results and derived conclusions~~.

The final step in the data driven decision making cycle is utilization by stakeholders who should actively utilize the produced results and conclusions to inform their actions and who should be the same who made decisions on to the evidence priorities set from the onset. The data driven decision making cycle is a cycle because ideally the utilization step can and should inform the evidence priorities in the priority setting step.

*[Narrative on bottlenecks, both general and context-specific, will go here*]

This section will show how an analytical framework – in our case in the form of a matrix – can be used to guide data collection and analysis in both a comprehensive and simplistic fashion. The selection of an analytical framework prior to data collection helps both guide the data collection processes as well as subsequent analyses.

Figure 3 Using the conceptual framework and data-driven decision-making cycle to address issues relevant for FSN

<table>
<tr><th></th><th>Define evidence priorities</th><th>Data (review, compile, collect as needed, analyze)</th><th>Translate and disseminate</th><th>Use findings to make decisions</th></tr>
<tr><td>Macro-level: Drivers</td><td>Identify which drivers and what about them are most salient for the identified problem, and nature of eventual decisions to be made</td><td rowspan="5">Minimal set of key indicators (existing or new; measurable and meaningful)<br><br>Key point 1 from section 2<br><br>Key point 2 from section 2<br><br>Key point 3 from section 2</td><td rowspan="5">Identify key stakeholders from relevant sectors from the outset<br><br>Key point 1 from section 5<br><br>Key point 2 from section 5<br><br>Key point 3 from section 5</td><td rowspan="5">How can prior translation be connected to feasible ideas related to decision making<br><br>Key point 1 from section 6<br><br>Key point 2 from section 6<br><br>Key point 3 from section 6</td></tr>
<tr><td>Systems level</td><td>Identify which aspects of health and food systems are most salient for the identified problem, and nature of eventual decisions to be made</td></tr>
<tr><td>Personal, HH, community considerations and decision making</td><td>Identify which aspects of personal, household (HH) and community considerations/decision-making factors are most salient for the identified problem, and nature of eventual decisions to be made</td></tr>
<tr><td>Individual level</td><td>Identify which dietary, nutrition, and health are most salient for the identified problem, and nature of eventual decisions to be made</td></tr>
<tr><td>FSN cross-cutting levels</td><td>Identify which of the 6 aspects of FSN are most salient for the identified problem, and nature of eventual decisions to be made</td></tr>
</table>

The primary aim of the matrix template – once filled in – is to identify problems that require data and can lead to specific actionable decisions.

The first step to be undertaken, prior to data collection, is to fill in the above matrix template by first identifying the necessary information related to the evidence priorities that are going to be related to the subsequent data collection, and associated evidence-based decision-making. The second step, still prior to data collection, is to identify the minimal set of new and/or existing key indicators that are *known* to be both measurable and meaningful. Still prior to data collection, from the outset, the third step is to identify key stakeholders from the sectors relevant to the information specified in the first column related to the defined evidence priorities. The last step prior to data collection is to critically think about how the expected results might be translated and connected to feasible ideas related to decision making that is linked to the evidence priorities defined from the beginning.

Here follows an example of how one might complete the matrix template that facilitates the concurrent operationalization of the conceptual framework and data driven decision-making cycle to address issues relevant for FSN. *The plan for this section is that an additional 2-3 example matrices would be provided such that examples will integrate different perspectives.*

EXAMPLE (1) Meat consumption identified as problematic in a population – too low in some groups resulting in micronutrient deficiency and too high in others with associated NCDs.

| Level | Define evidence priorities | Data (review, compile, collect as needed, analyze) | Translate and disseminate | Use findings to make decisions |
|---|---|---|---|---|
| Drivers | - Environmental considerations of nutritious ASF* production<br>- Trade and ag related policies<br>- Socio-cultural (consumption preferences) | - Production, water and land use<br>- Relevant policy (e.g. exist, and/or enforce)<br>- [Barriers to consumer change] | - Engage key stakeholders: Agriculture, trade and industry, social protection, health sector | - Ag innovation opportunities<br>- Adaptations to social protection efforts/ new policies<br>- Diet and health campaigns (e.g. to shift preferences to nutritious ASF) |
| Systems | - Producers and supply chains, including retail and market structures, cold chain<br>- Health service coverage and existing diet-related actions | - Per capita supply of nutritious ASF<br>- Prices and trends<br>- [Market structures] | - Engage key stakeholders: Agriculture, food industry, health sector | - Supply chain adaptations (e.g. cold storage)<br>- Industry incentives and penalties<br>- Health sector to reinforce messaging |
| Personal, HH, community | - Local producers and supply chains<br>- Double burden at HH level | - Supply of nutritious ASF at local (farmers) markets<br>- Single vs. multiparent HH<br>- Community groups | - Engage key stakeholders at local level: Municipal governments, Municipal health systems, Farmers markets | - Local health sector to reinforce messaging<br>- Messaging at farmers markets<br>- Farmers markets incentives |
| Individual | - Extremes of ASF consumption can be direct cause of micronutrient deficiencies (e.g. too little) and NCDs (e.g. too much, highly processed) | - NCD and micronutrient deficiency prevalence<br>- Dietary intake patterns | - Population disaggregated data essential to understand issues and propose solutions<br>- Engage key stakeholders: health sector, … | - Data used for advocacy, and to raise awareness of issues and relation to dietary intake |
| FSN cross-cutting | - <u>Access</u> key for those with very low consumption<br>- <u>Sustainability</u> key for those with any ASF consumption | - Availability/access of nutritious ASF (e.g. seasonality; trends)<br>- [nutritious ASF preferences]<br>- [Short and long term risks to access etc.] | - Population disaggregated data essential to understand issues and propose solutions<br>- Engage key stakeholders: consumer groups, … | - Data used to inform actions at driver and systems level – ensuring unique conditions of population sub-groups considered |

EXAMPLE (2) Fish consumption identified as problematic in populations with domestic access to fish

[To be completed]

EXAMPLE (3): Emergency / conflict situation in which healthy dietary intake is compromised

[To be completed]

EXAMPLE (4): (if needed) suggestion welcome

[To be completed]

## 2. A REVIEW OF EXISTING FSN DATA COLLECTION AND ANALYSIS INITIATIVES

Many existing data platforms and collection systems are relevant for FSN. In this chapter we will review existing and on-going efforts to collect, consolidate, and enhance access to data relevant for FSN. We will provide an overview of multi-country data sources (upper section of Table 1), identifying the primary domain of the data (distal, proximal, immediate, individual – as per the conceptual framework in Figure 1). Examples of national efforts to strengthen data for decision making in FSN are also summarized (Box 2.1). While many efforts exist, there are important challenges and barriers to the effective utilization of such data for decision-making for FSN. These challenges will be reviewed briefly, followed by an overview of existing and on-going efforts to address them (lower section of Table 1). For each, the primary focus of the effort across the data driven decision making cycle (Figure 2) will be identified. Finally, a reasoned review approach will be used to discuss pros and cons of current set of efforts and assess the extent to which they are aligned with priorities, address the identified challenges and barriers, are mutually complementary, and identify gaps and redundancies.

Several challenges exist at each of the four stages of the data cycle for FSN (Figure 2). Several critical issues hold relevance across all stages in the data cycle and are dealt with in depth in other chapters of this report. Specifically human and financial resources and capacity (see Chapter 3) and governance of data for FSN decision making (Chapter 5).

Priority setting:

- **Lack of coordination:** As noted in Chapter 1, multiple stakeholders and sectors are relevant for FSN, each with their own frameworks, classifications, typologies, ontologies. There is overlap, complementary, but also gaps to ensure a comprehensive approach to FSN. We seek to address this in part by presenting in section 1 a conceptual framework of how these fit together. (See chapter 5)
- **Lack of clarity on how to prioritize**, and how to align potentially competing priorities across relevant sectors that compile and use data relevant for food security and nutrition (e.g., agriculture, social protection, health, industry and trade). (See chapter 3)

Gather, curate, analyse data (see chapter 3):

- **Poorly conceived / inappropriate indicators:** There is often a lack of sufficient attention to define the constructs to be measured and ensuring that appropriate valid indicators are used. (See chapter 3, section 3.3)
- **Poor data quality:** Existing data sets are often not reviewed and data range checked to ensure plausibility of values for all indicators. Common data types (e.g., dates) are often collected in non-standard manner creating issues for merging or comparing data sources.
- **Timeliness:** Where primary data is needed, data collection and analysis can be a slow process and may not permit timely decision making. This may be a particular problem in emergency and crisis situations.
- **Data collection ethics:** Data collection must follow good practice in terms of ethics data protection. With the expanded use of mobile and electronic methods for data collection and sharing, this can present specific challenges. (See chapter 4)

Translation;

- Data is often presented in complex graphics / tables, with considerable detail, and the needed steps to glean decision-focused conclusions from that data is often insufficient.

Utilization:

- **Lack of access to data:** Many data sets and the outputs of data review, consolidation and analysis (publications, and other resources) are not publicly available. This includes data from the public and private sector and from research. Sometime justified reasons (e.g., data protection of farmers) hinder its open publication but often data could be made available if data sets would be anonymized properly.

- **Data protection:** Data de-identification and storage must also follow good practice in terms and data protection laws and standards. With the expanded use of cloud storage, and data sharing through open access platforms this can present specific challenges. (see Chapter 3).

**Conclusions and implications**:

(To be completed)

Box 1 Examples of national/ regional efforts that have supported data generation and utilization related to various aspects of FSN [inserted here as example from India – we will identify and review several options]

The POSHAN network in India has the objective of "…generating, synthesizing, and mobilising nutrition data and evidence, by engaging a variety of stakeholders, to support strategic nutrition policy and programme actions in India." Led by IFPRI Delhi, funded by BMGF, https://poshan.ifpri.info/about-us/our-approach/

### Box 2 Data collection in conflict settings

Armed conflict and other situations of violence have remained one of the primary drivers of food insecurity, malnutrition and famine. All five famines declared over the last decade in Ethiopia, Nigeria, Somalia and South Sudan were essentially driven by the consequences of armed conflict and violence. Hotspots for violence tend to be blind spots for information especially for survey and household data, which in turn are necessary to ascertain the severity of the situation and declaration of famines. Challenges in this regard are multiple and concurrent: data may be impossible to collect, collected but not released, or collected but lacking in completeness, quality, or timeliness. Remote methods are increasingly viable in terms of their utility to support data collection in areas where people cannot go, but usefulness and accuracy of these to estimate the severity and magnitude of crises are still limited.

The IPC recommends that a combination of sources of evidence should be used to the extent possible. Data should be collected during a mission to an area affected by conflict if that is an option. Helicopter missions, for example, were crucial to classify the 2016 Famine. Indirect assessments based on the recording of new arrivals and interviews in refugee camps are also useful, but the processing of the information gathered needs to carefully consider origin and travel time of the refugees. Evidence from similar nearby areas or camps as well as historical trend analysis and evidence collected in distribution points should be also considered.

There is also likely an entire ecosystem of conflict data collection and analysis unique to a given context. Data on the extent of the conflict itself (number of people involved, causalities, etc.) may be more available than data on the food security and nutrition status of the affected population. Many conflict contexts have a range of publicly accessible reporting by various UN bodies, including Panels of Experts mandated by the UN Security Council, Joint Mission Analysis Centres or Human Rights Divisions within UN peacekeeping operations, and other analysis by specialized agencies. Such as the International NGO Safety Organisation (INSO), and the Nigeria Security Tracker. A variety of academic and other research institutions also provide conflict analysis and other analysis directly relevant to conflict analysis, such as the Rift Valley Institute's work across the Greater Horn of Africa. Regular media reporting can also supplement these sources.

## Table 1 Existing initiatives on data for FSN

(This is a preliminary list of existing initiatives on data analysis and collection tools for FSN, to be completed)

| Initiative/group | Domain (from figure 1.1) | Step in data cycle (from Figure 1.2) | Primary objective | Host | Members/ partners | Funding | Resource(s) |
|---|---|---|---|---|---|---|---|
| Multi-country sources of data for FSN | | | | | | | |
| FAOSTAT | Distal, Proximal, and immediate | Data consolidation and curation | Provide open access to food and agricultural data covering 245 countries and territories. It comprises 11 different food and agriculture data domains:<br>- Agricultural production<br>- Food Security and Nutrition<br>- Food Balances<br>- Trade<br>- Prices<br>- Land, agricultural inputs and sustainability<br>- Population and Employment<br>- Investments<br>- Macro-economic indicators<br>- Climate change<br>- Forestry<br>Plus a dedicated section on SDG indicators under FAO custodianship | FAO | | FAO Regular Programme (Various trust funds may contribute to the generation of data for individual domains) | https://www.fao.org/faostat/en/#home |
| Global Diet Quality Project | Individual (diet quality) | Data collection | | GAIN | Gallup, Harvard University | Multiple | https://news.gallup.com/opinion/gallup/321968/global-diet-quality-project-aims-bridge-data-gap.aspx (project website Under development) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| EAF Nansen Programme | FSN, Systems | - -priority setting<br>- -data quality<br>- -translation<br>- -utilization | The long-term objective (or Impact) of the EAF-Nansen Programme is that "Sustainable fisheries improve food and nutrition security for people in partner countries". | FAO - FIAF | EAF-Nansen Programme<br><br>FAO | Norwegian Agency for Development Cooperation | http://www.fao.org/in-action/eaf-nansen/en |
| Aquatic Food Composition Database | FSN | Data | This database synthesizes existing nutrient composition data for aquatic food species. These data originate from disparate sources, including national food composition tables (FCT), international datasets from FAO, and other peer reviewed published sources of nutrient composition | Harvard Univ. | | | https://dataverse.harvard.edu/dataverse/afcd |
| Global Action Network Sustainable Food from the Oceans and Inland Waters for Food Security and Nutrition | FSN/All | Utilization | This Global Action Network will mobilize actions to include aquatic food as a key food source for achieving food security and improved nutrition in the Decade of Action on Nutrition (2016-2025) and in line with the UN Sustainable Development Goals (SDGs | Norwegian Ministry of Trade and Fisheries | | | https://nettsteder.regjeringen.no/foodfromtheocean/ |
| Efforts to address data-related challenges and barriers | | | | | | | |
| Technical Advisory Group on Nutrition Monitoring (TEAM) | Individual | - -priority setting<br>- -data quality<br>- -translation<br>- -utilization | Advise WHO and UNICEF on how to improve the quality of nutrition monitoring efforts at all levels | WHO/ UNICEF | Experts identified and assigned for 3 to 5 year terms | WHO/ UNICEF | https://www.who.int/groups/who-unicef-technical-expert-advisory-group-on-nutrition-monitoring |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| International Network of Food Data Systems (INFOODS) | | Data quality | To improve the quality, availability, reliability, and use of food composition data | FAO | Government organizations, research institutes, universities, international organizations, foundations, and professionals working on food composition issues | ? | https://www.fao.org/infoods/infoods/en/ |
| DataDENT | Individual | - -priority setting<br>- -data quality<br>- -translation<br>- -utilization | "…aims to transform the availability and use of nutrition data by addressing gaps in nutrition measurement and advocating for stronger nutrition data systems" | JHU | IIP/IFPRI/R4D | BMGF | https://datadent.org/about-us/ |
| INDEXX | Individual | Data collection and utilization | "…strives to increase the availability, accessibility, and use of dietary data through the development of an innovative data collection platform and demonstrating uses of existing consumption data for policies and programmes" | Tufts Univ. | | BMGF | https://inddex.nutrition.tufts.edu/inddex-project |
| IMPROVE | Individual | Data | "…aims to improve evidence, estimates, and programming for maternal, new-born, child, and adolescent health and nutrition" | JHU | | BMGF | https://www.jhsph.edu/research/centers-and-institutes/institute-for-international-programs/current-projects/improving-measurement-and-program-design/ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Countdown to 2030 | All (?) | Translation | "…to track progress of life-saving interventions for reproductive, maternal, new-born, child and adolescent health and nutrition." | JHU | [managed by core staff] | UNICEF, BMGF, USAID, NORAD | https://www.countdown2030.org/about |
| Food Systems Dashboard | Systems; Interface | Translation; Utilization | "… combines data from multiple sources to give users a complete view of food systems" | GAIN/ JHU | Multiple partners | Multiple | https://foodsystemsdashboard.org |
| SUN MEAL | FSN; Individual (?) | Data | SUN MEAL system will be the means for measuring the extent to which the SUN Movement is achieving results and impact | | | | https://scalingupnutrition.org/progress-impact/monitoring-evaluation-accountability-learning-meal/ |
| 50x2030 Initiative | | Data collection, dissemination and use | Support 50 countries by 2030 to collect and disseminate agriculture and rural statistics<br>Increased and sustained evidence-based decisionmaking by promoting the use of the data | WB | (FAO, WB and IFAD) | | https://www.50x2030.org |
| Hand-in-Hand Geospatial Platform | | Data integration and federation | Provides integrated data services, advanced geospatial modeling and analytics. Supports Tabular (location+geocode) and Geospatial (raster+vector) in both multi-dimensional and attribute list data structures/formats | FAO | FAO and partners | | https://www.fao.org/hih-geospatial-platform/en/ |

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| CGIAR Platform for Big Data in Agriculture | | | Embracing big data to provide information for food security and other development issues | CGIAR | CGIAR Research centers, programs and Big Data Partners | | http://bigdata.cgiar.org/ |
| Global Open Data for Agriculture and Nutrition (GODAN) | | | Harnessing open data for agriculture and nutrition | | Various private and public sector and civil society organizations | | https://www.godan.info/ |

# 3. Capacity constraints for effective FSN data collection and analysis at local, country, and global levels

The constraint of insufficient capacity that exists at the country and global levels affects all stages of the data value chain. Factors that impede sufficient, timely and good quality data collection and analysis to accurately reflect food security and nutrition status, their causes, and charting changes over time, can be a barrier to identifying actionable targets for intervention. Data gaps prevent decision-making to formulate policies to improve human and planetary health. Policy making is difficult because of lack of situational data and also due to the paucity of data on interests and values of actors (Deconinck *et al.*, 2021).

## 3.1. Local and country-level capacity constraints

At the **country level**, five major constraints arise are commonly observed. These include: (i) insufficient resources (financial, human capital and research infrastructure), (ii) social divides in digital access and literacy, (iii) the lack of coordination among the agencies involved in collecting and analysing data (iv) the lack of political will/keenness to capture sensitive data, and (v) limited efforts at stakeholder engagement

### 3.1.1. Insufficient resources for data collection

#### Financial constraints

Providing sufficient financial resources is key for the development and validation of data collection tools, establishment of database and its management and for the data collection, analysis and dissemination process. Allocation of the necessary financial resources from the public budget may be limited in many developing countries that have a limited tax base. (See https://agsci.colostate.edu/smallholderagriculture/financially-stalled-governments/). Where they exist, national research funding programmes are also less likely to invest in food security, nutrition and health promotion-based research as these are not easily marketable (Neema and Chandrashekar, 2021). This lack of funding can affect the data value chain in various ways from priority setting, data generation to data dissemination. It can result in absolute lack of data or lead to poorly executed data which does not appropriately fill knowledge gaps or inform decision making. Academia can lead efforts to fill this gap by prioritising research on food security and nutrition including identifying optimal dietary targets and cost-effective policies for health and nutrition. Such efforts could include monitoring and evaluating health indicators and policy outcomes. By fostering partnerships with communities, and engage with advocacy groups, the media, business, and policy makers; academia would be well to inform and advice government and industry efforts. (Mozaffarian et al., 2018).

Insufficient allocation of funding in the national statistical plan to collect food security and nutrition data and to train human capital to carry out these responsibilities is a major stumbling block in many developing countries. Financing data reviewed by the Secretariat of the Partnership in Statistics for Development in the 21st Century (PARIS21) for the last decade shows that, while external partners have increased their commitment to statistics, the effort is poorly co-ordinated. While economic and demographic statistics have received majority of the recent funding, environmental statistics had less allocation (OECD, 2019). It is estimated that 90% of national statistical agencies in low- or lower-middle-income countries lack agricultural data due to funding limitations (Kalibata and Mohamedou, 2021). This is a lost opportunity in terms of collecting data that can inform planning, budgeting and policy making in this vital sector. Sometimes budgetary and time constraints result in inappropriately sampled small surveys with poor generalizability.

## Box 3 The high cost of FSN surveys

Household surveys that provide key information on respondents' dietary intake and nutrition status could require enumerators to perform individual nutrition assessment (collecting anthropometric, biochemical, clinical assessment and dietary intake data). Training the enumerators and implementing the necessary field operation is a costly and labour-intensive process. Similarly, agricultural surveys that seek to reach small farmers in interior areas require the mobilization of many enumerators and involves covering larger travel distances, all of which increase the overall survey costs. While newer methods such as the use of smartphones may reduce the time spent in face-to-face data collection, and therefore potentially reduce the number of needed enumerators; it is important to evaluate disparities in the ownership of digital devices and the access to technology and knowledge among the vulnerable groups including women and small farmers.

In multi-ethnic populations, many languages are spoken and understood within the country or even the region surveyed. This adds a layer of complexity to the process of data collection (such as validation of tools, language competencies of the enumerators, etc) and is expensive. When these demands arise in the context of existing financial constraints, a compromise that prioritizes feasibility over representativeness is usually reached. In many countries, the cost of validating dietary assessment tools such as frequently used food frequency questionnaires or screeners with objective biomarkers has the consequence that there are limited validation efforts. This has often led to casting doubts on the quality of the data and thus the validity of results arising from the dietary surveys.

Dietary data needs further processing in terms of nutrient analysis linking dietary data to food composition tables. Nutrient analysis of food to create comprehensive food composition databases is in itself an expensive undertaking and unaffordable to several low-income countries.

The lack of financial resources in several countries has also resulted in many of the SDG indicators being replaced with proxy indicators. This hinders cross-country comparisons and at times the proxy indicators are poor surrogates for the original indicators making their interpretation challenging for the required context.

### Human resource and manpower constraints

The lack of adequate human capital both in terms of manpower and their ability (possessing the required level of competency) is also cited as a major constraint at the country level. Human resources and staffing are important aspects of data collection using the traditional survey methods. Nutrition and food security data collection requires adequately trained personnel. For instance, dietary data collection requires specific skills including the ability to choose the appropriate and use a dietary assessment tool for data collection, assist respondents in estimating portion sizes and ensure completeness of the reporting. Dietary assessment requires other skills such as the ability to choose an appropriate food composition database and substitute a closely matched food/database when local data is unavailable.

Enumerators conducting household surveys also require interpersonal skills and domain knowledge to engage with respondents, build trust and ensure completeness and accuracy of data. Nutrition assessment also requires specific skills such as performing anthropometry and requires trained personnel. This need for adequately trained competent personnel cannot in all instances be offset by the use of technology.

It has been claimed that recourse to technology to allow interviewing people from remote location, such as telephone or internet-based, might reduce the need for human resource. This is only very partially true, if at all. Reliable measurement of outcomes such as anthropometry or assessment of nutrition-focused physical findings, or the measurement of the local food environment will always require the physical presence of the enumerators at the location. Furthermore, proper use of remote technologies to conduct interviews may impose the requirement of additional, different kind of skills, on which enumerator still need to be trained.

National statistical organisations are oftentimes overwhelmed by **competing priorities** that limits their attention to agricultural statistics. This is especially so in developing countries where inadequate funding further stresses the organisational capability and makes it important to prioritise. For developing countries, it is noted that agriculture and food data is important and that it is also important to link food security data to livelihoods and poverty (Committee on World Food Security, 2021)

### Inadequate research infrastructure

Insufficient funding and the lack of well-trained human capital often determine an inadequate state of the research infrastructure that is required, at the national level, to support every stage of the data value chain (Figure 2). The inadequacy of the research infrastructure typically becomes evident in terms of: lack of research quality frameworks and methodological expertise for timely, relevant, and sufficient data collection; lack of prior data; lack of data processing and analytical capabilities at the institutional level; and poor practices relating to data dissemination and communication.

The **lack of robust research quality frameworks** at the National Statistics Offices and other agencies involved in food security and nutrition data collection results in improper survey methodology such as sampling, data collection methods, data verification, management and analysis. Several countries report dietary data with poorly planned methodologies such as the use of cross-sectional design for national surveys restricts the evaluation of causal drivers of food security and nutritional status and changes over time. Well-designed prospective studies that help evaluate nutrition-specific or nutrition-sensitive interventions to accurately understand causal and temporal nature of the drivers involved are lacking to firmly support evidence-based decision making in many countries (Nutrition and Food Safety, WHO/UNICEF Technical expert advisory group on nutrition monitoring (TEAM), 2020). Specifically with regards to global food security and nutrition data, several gaps and the lack of its usability (the extent to which a system or product can be used with effectiveness, efficiency and satisfaction) when it exists, have been identified. The reasons behind such challenges are multifactorial (Micha et al., 2018).

Reliability and availability of food security and nutrition data are also often limited due to the **lack of data processing and analytical capabilities**. Without a full understanding of the statistical principles and methodological aspects of a survey and lacking the analytic capabilities and the capacity to interpret and communicate the data at the level of individual data producers and policymakers, for example, effective data-driven decision making will be strongly hampered. The collection of multi-dimensional big data sets also introduces complexities that may require upskilling of the current staff. Insufficient capacity to disseminate, interpret and communicate data adds barriers to advocacy efforts for continued investment in food security and nutrition-related data collection. Concrete examples of this constraint are seen for example in the analysis of dietary assessment data. Traditional analysis of dietary data involves taking a series of steps: First the dietary assessment data obtained for each food eaten using household measures is converted into a corresponding weight measure. This weight is then used calculate the nutrient intake from the specific food by comparing the data against food composition tables. The series of steps and conversions have the potential to introduce many errors. Accuracy of analyses of dietary data was enhanced in the last few decades by the use of nutrient analysis software that convert the food consumption information to nutrient intake data. Recent technological advances in dietary assessment have integrated the various steps in dietary analysis including the entry of food consumption data during the participant interview and the subsequent nutrient composition calculation with specific dietary analysis platforms that have offline and online capabilities (https://www.fao.org/infoods/infoods/software-tools/en/). This integration of several steps traditionally undertaken in analysis of dietary data and the automated nutrient calculations reduces errors arising for manual data entry and it subsequent transcription. However, many of these software that allow for modular usage of local food composition databases are not open access. The lack of affordability limits their widespread uptake in low-middle income countries. Similarly, while the use of dietary biomarkers improves the accuracy of dietary intake estimations, its implementation requires extensive sample collection, storage, transportation, processing and analytical abilities. These advances in dietary assessment methodologies while improving the accuracy of dietary intake estimations, also increase the requirements in terms of human, financial and technological capital. Therefore, the feasibility of large-scale adoption of these advances may be a challenge for LMICs. Finally, analyses of micronutrients in food require sophisticated methods and are prohibitively expensive to the LMICs. This lack of food analytical limits the nutrients listed in the food composition tables of many countries. After data collection and analysis, results are often communicated only in the form of tabulated data, with relatively little interpretation and analysis (FAO, 2015; OECD, 2019). While there is an increasing awareness of the importance of supporting data use with proper analytical briefing on how the data are obtained from elementary information (Sethi and Prakash, 2018), the lack of such products can hamper data-driven policymaking and targeted interventions to address the problem (FAO, 2015). Given that only 50% of national statistical offices (NSOs) in the lower-middle statistical capacity level monitor the use of their data (Sethi and Prakash, 2018), it is difficult to gauge the actual utility of the data. The FAO provides statistical support and countries in the Southeast Asian Region have shown the highest gains in terms of statistical competency over the last decade(OECD, 2019). However, the delivery of support to build capacity is limited by the narrow assessment of capacity of national statistical systems. Statistical assessments traditionally focus on skills for statistical production processes, quality assurance and codes of conduct, legislation, principles and institutional frameworks. Skills restricted to these domains may be insufficient with the emergence of advanced technologies in data production with increased complexity, and the involvement of new data providers and users. There is also a lack of emphasis on data communication and dissemination. The methodological advances in the data ecosystem and their appropriate dissemination requires soft skills, such as management and leadership.

The complete lack or the insufficient coverage of prior data in many areas related to food security and nutrition makes assessment of trends and or arriving at informed decision for policy challenging. In FSN, in particular, the areas where lack of sufficient data is particularly relevant include fundamental data such as on food composition; food availability; and those relating to impact of pests, natural calamities, climate change, conflicts or other shocks on food security and nutrition. The availability of agri-food data and statistics is, in general, far from complete. It ranges from annual agricultural survey data, being available for approximately 60% of the countries, to humbling figures of less than 4% for productivity and income of small-farm holders, food loss, food waste, secure right over agricultural land. Overall, the reporting rate for the 21 SDG indicators under FAO custodianship, in 2020 was only 51% (Committee on World Food Security, 2021). Among these, data on the extent of food losses and waste have important impacts on food security and nutrition policy. In this area, countries may need to ensure cost effective data generation, improve the reliability of data to benchmarked international standards in terms of methods and metadata, enhance the accessibility of information for policymaking, and encourage transfer of innovative practices among countries and improve transparency (Fabi *et al.*, 2021).

The availability of “downstream” data relating to the food systems such as consumer behaviour and what drives, impact of household interventions to reduce food water/loss for instance, food utilisation data or dietary diversity data are even more scare (Committee on World Food Security, 2021; Deconinck *et al.*, 2021). Data on the evaluation of impact of food policies or estimation of economic losses due to malnutrition and the cost effectiveness of nutrition-specific and nutrition sensitive intervention are also largely lacking.

### Box 4 The lack of data for nutrition assessments

An important domain of nutrition assessment is an accurate estimation of dietary intakes in populations. Data in this area is inconsistent, outdated, incomplete national food composition databases, or support for institutions involved in developing the databases, challenge the accuracy of nutrient intake estimations in various countries and prevent its utilisation by multiple users. The lack of comprehensive food composition databases with adequate representation of both plant, aquatic, and land-based animal foods consumed in the country, makes many countries rely on the databases of the neighbouring countries or global databases for the estimation of nutrient intakes. Inadequate food composition data and their use may then lead to erroneous research results, wrong policy decisions (particularly in nutrition, agriculture and health), misleading food labels, false health claims and inadequate food choices (Charrondiere, 2017). The Malabo Montpellier Panel report stated clearly that the ‘African governments lack the necessary data to combat malnutrition, few nations collect data required to inform decision makers about what people eat, and there is no functioning global dietary database’ (Malabo Montpellier Panel, 2017). A recent review on global dietary surveillance (Micha *et al.*, 2018) confirms and identifies the non-availability or inadequacy of country-specific food composition tables (FCT)/food composition database (FCDB) as one of the major data gaps and challenges for the limited availability of global dietary data which are necessary for a wide variety of purposes, including to ‘model, design and implement specific dietary policies to reduce disease and disparities in different nations’. In these cases, strengthening regional collaborations and the establishment of reference. In such cases, strengthening regional collaborations and the establishment of laboratories may provide a cost-effective solution. Lack of representation of indigenous and forest foods in food composition databases is an important deterrent to accurately evaluating dietary intakes in indigenous populations (FAO, 2013b). INFOODS tackles constraints in paucity of food composition data and data quality through an exemplary coordinated effort (https://www.fao.org/infoods/infoods/en/) (Refer Box 5 on page 17)

Data when available, may be insufficient. One such domain relates to food safety, which is integral to food security, nutrition and health in many countries. The Codex Alimentarius was established by the Food and Agriculture Organization (FAO) and the World Health Organization (WHO) to protect consumer health and promote fair practices in global food trade. Low- and middle-income countries often lack resources to invest in improving their own national food safety regulatory frameworks and therefore rely on Codex standards as the basis for their national food safety legislation. However, the Codex standards may overlook practices that are common in small-scale food production and their connected value chains. Both the European Food Safety Authority (EFSA) and Codex Alimentarius have databases containing food safety parameters, but these are not available open access. This kind of data may be regarded sensitive to a country as levels above maximum limits can result in export bans and affect trade. Also, cost and resources for monitoring programmes are major constraints in enabling timely and relevant data collection related to food safety.

Data may be insufficient because it lacks the granularity to make group-specific decisions. For example, nutritional status in specific groups and over a long enough period to track trends may be unavailable while overall estimates exist. Furthermore, the level of granularity required to evaluate disparities in nutritional status say for instance by gender are currently absent in many countries (MTR Foresight report 2020; UNSCN 2018). There is a need for individual-level data to track progress not only on food security and nutrition, but also on gender equality and women’s empowerment. For example, the Women's Empowerment in Agriculture Index (WEAI) metrics on both women and men enables to track gender equality and transformation of gender norms (The Women's Empowerment in Agriculture Index: A suite of tools and methods for measuring empowerment and gender equality, Hazel Malapit: IFPRI, Senior Research Coordinator).

Similarly, agricultural data mainly obtained through interviews with farmers or through surveys, often lead to biases over time due to the over-representation of the larger farm holders and lack of sufficient representation of the small farmers. Such cropland data when used by policymakers for decision making to meet the growing demand for food is inaccurate and does not represent the needs of the smaller farms. Smallholder farmers in developing countries also lack quantitative and qualitative data on the production and sales of all crops due to limited access to information technologies. This is a serious limitation to research and policy that is aimed at poverty and hunger-reduction. To improve reach, granularity and affordability, some countries have developed accessible digital technologies for monitoring food security that helps bridges many of these constraints improving the granularity of the data while making it a simple and affordable process. One such example is the SATIDA (Satellite Technologies for Improved Drought Risk Assessment) project was developed to support Doctors without Borders. (See Box 5 on page 17). At the regional and national levels, timely and granular data that allows for evaluation of impact of innovative value-chain solutions and factors that can improve their uptake are also lacking (Committee on World Food Security, 2021, Keynote Presentation by Maximo Torero Cullen, FAO Chief Economist).

The biodiversity is the agroecosystem's main component, and improving supportive management practices in food production systems maintains ecological health (Gemmill-Herren, 2020). The agrobiodiversity Index (ABDI) approach is used to collect data, providing information to stakeholders, businesses, and policymakers about the consumption and markets, production systems, genetic resource conservation. However, there is a lack of globally consistent data for several vital components of agrobiodiversity, including consumption, production, and less reliance on local and wild species. Therefore, shared international data collection, detailed analyses, and reporting systems are required to help fill critical data gaps (Jones *et al.*, 2021).

### 3.1.2. Social divides in digital access and literacy

The management of data flows requires modern data infrastructure at the national level, which is less established in low-income countries. Due to lack of access and usage of broadband infrastructure in some developing regions such as Sub-Saharan Africa and South Asia, internet usage gaps as high as 49% and 64% respectively (Lishan Adam and Michael Minges, 2018). Newer digital technologies may therefore pose specific challenges to LMICs owing to existing social gradients that limit technology penetration, access, and user awareness. Social divides in digital access and literacy at the national levels is a further impediment to reaching vulnerable stakeholders such as women or small farm holders (LeFevre *et al.*, 2021). Thus, while technological advances may reduce cost and widen the reach of surveys, the social divide may lead to the underrepresentation of those with poorer digital access and literacy (LeFevre *et al.*, 2021) Policies and interventions that are based on such data generated from skewed sampling are therefore not useful to the unrepresented stakeholders who may have the utmost need for data-driven policy and support (Bell *et al.*, 2017; LeFevre *et al.*, 2021).

There have been advances in methods used to collect and instantaneously process food production including agricultural data are through the use advanced **sensor technologies and digital agriculture**. Aquatic food is a vital source of food for people, and fish production requires constant monitoring and ready to use data. Such data access will prevent overexploitation or depletion of fish stocks and provide valuable information for effective fisheries management

(Grilli, Curtis and Hynes, 2021). Moreover, smart livestock farming also uses several technologies that analyse data to improve production with reduced environmental impacts. For example, new data analytic architectures that generate farm and field level data allows farmers and stakeholders to monitor processes and make a decision for the precision livestock farming. (Fote *et al.*, 2020). The use of these advanced technologies provides a level of granularity and immediate access to data that was lacking in traditional surveys. However, the use of modern techniques such as big data may pose further challenges to data curation, analysis, translation, and dissemination at the national level when the research infrastructure is lacking.

The efficiency of instantaneous data that comes with the adoption of latest technologies may also pose ethical problems in the absence of quality assurance and governance. For instance, the smart information system (SIS) harnessed the capabilities of big data and artificial intelligence (AI) to provide farmers various data such as farm efficiency, local weather predictions, and detection system for pests and disease. This was thought to enable quick and improved decision making for the farmers. However, ethical concerns, including the lack of accuracy of SIS that could cause the harvest lost, livestock disease, and low crop productivity have been raised by the stakeholders. Moreover, it is feared that SIS may replace human jobs (Mark, 2019). Thus, it is imperative that there is proper planning and establishment of robust quality assurance frameworks and governance structures before novel technologies can be successfully support decision making.

In other instances, the digital technologies employed may be designed without obtaining user input. This is problematic when knowledge and technological divides across the stakeholders are not bridged through appropriate engagement. In such circumstances, the efforts to harness latest digital technologies, therefore are limited in their understanding of working conditions, requirements, and end-user expectations. The deployment of the digital technologies may sometimes take the focus and spending away from the major objective which is to improve nutrition and health of the population for instance. end-users may sometimes not have the connectivity, familiarity with or digital literacy required to operate these devices. Also, continuity of efforts is needed to evaluate the benefits of technological intervention. In case of replacement or updating of a software/application/ device, the advantages and benefits of the previous version and the need for improvement should be considered in tandem for the revised version to be useful and accepted by the end-users. (Johari, 2021).

### 3.1.3. Lack of coordination between agencies

Collection of food and nutrition indicators related to the Sustainable Development Goals (SDG), such as the prevalence of underweight, health outcomes, dietary surveys and agricultural indices, may involve multiple agencies within a country. The lack of a coordinated effort between these agencies at times, leads to duplication of the efforts. Moreover, it hinders the interoperability and linkage between datasets required to have a holistic understanding of food security and nutrition status and their drivers in a population. Some of the required data may be collected by academia, involving individual researchers whose smaller surveys may not necessarily aim to be reflective of the nation at large. Other data may be collected by the private agencies and may be archived behind a paywall, limiting access to stakeholders. Collaboration among stakeholders of sustainable agri-food supply chain management including farmers, policymaking organisations, as well as research institutions based on data sharing activities, trust, commitment, coordination and stability and joint efforts, facilitates achievement of food security, business and environmental outcomes (Dania, Xing and Amer, 2018).

### 3.1.4. Lack of political will and transparency

Moreover, the lack of political will and hesitancy to share sensitive information prevents the collection of data such as moderate food insecurity for the fear of implying challenges far greater than those perceived and accepted by the national governments. In other instances, access to food safety data may be regarded as sensitive information as levels above maximum limits may affect export. The impetus for financial and institutional support from policymakers to collect good quality data, adhering to the four foundational principles of Findability, Accessibility, Interoperability, and Reusability (FAIR) can be had if the benefits of good quality data collections and the opportunity cost of not doing so is internalized and well-communicated by the agencies involved. This requires champions from within the agencies who will provide sufficient drive and traction for the initiation and sustenance of such data collection efforts.

### 3.1.5. Lack of stakeholder engagement

Finally, the usability of the data is limited when stakeholders have not been involved in the survey planning and there is inadequate dissemination or access to information on what data is available and how it can be used by the stakeholder. These limitations to the access and use of data for improved decision-making, make it difficult to advocate for further funding and commitments towards the collection and analysis of food security and nutrition data.

## Box 5 Exemplary practices in tackling existing constraints

**Tackling constraints in data generation**

SATIDA COLLECT (https://m.apkpure.com/satida-collect/com.satida.collect.android) is an Android application that allows for rapid and simple collection of data related to malnutrition, and access to resources to support humanitarian aid organisations involved in drought and food security management. SATIDA COLLECT is a freely available, flexible, and efficient mobile application was developed using and open-source toolkit for data collection "Open Data Kit (ODK) aggregate". SATIDA COLLECT also standardises data collection on malnutrition, socio-economic factors, access to resources, food prices, coping capacities and other related data. All assessments using SATIDA include GPS coordinates and are automatically uploaded to a database for storage. Its application programming interface (API enables data to be immediately displayed on web viewer The SATIDA database provides immediate access to the data and allows further analysis through features that enable sharing and export of assessments. In addition, it facilitates the visualisation of drought risk with satellite-derived data. More importantly, from the user standpoint, it is an easy-to-use tool. SATIDA Collect was used in Central African Republic for monitoring food Security and analyse the drought risk and impacts. (Enenkel *et al.*, 2015)

**Tackling constraints in food composition data availability and quality**

The International Network of Food Data Systems (INFOODS) (https://www.fao.org/infoods/infoods/en/) was established in 1984, aiming at stimulating and coordinating efforts to improve the quality and availability of food composition data globally. The network provides guidelines (e.g., quality assessment of data from journal articles for use in food composition tables, food matching, conversion of units), and standards (e.g., food nomenclature, terminology, classification systems, tag names), overview of food composition data management systems and software tools for dietary assessment. In addition, a comprehensive e-learning course on food composition data is available on their webpage.

**Engaging stakeholders**

The EAF-Nansen Programme (http://www.fao.org/in-action/eaf-nansen/en) is a partnership between the Food and Agriculture Organization of the United Nations (FAO), the Norwegian Agency for Development Cooperation (Norad), and the Institute of Marine Research (IMR), Bergen, Norway, for sustainable management of the fisheries of partner countries (http://www.fao.org/in-action/eaf-nansen/en). The long-term objective is that "Sustainable fisheries improve food and nutrition security for people in partner countries". The programme has since 1974 provided an opportunity for coastal low- and middle-income countries to assess and manage their fisheries resources, and in 2017 the theme "nutrition and food safety" was implemented in the science plan (Moxness Reksten *et al.*, 2020). Fishes are sampled on the research vessel Dr Fridtjof Nansen, and most of the samples are analysed at the accredited laboratories at IMR. As part of the capacity building embedded in the programme, local scientists and students can get funds to pursue a Master or PhD and take part in mentoring programmes. The results may assist national food authorities to evaluate the beneficial effects of nutrients against any potentially negative effects of contaminants or biohazards and guide officials tasked with regulating aquatic foods for both local consumption and exportation.

**Effective collaboration**

A 4-year longitudinal investigation in rural Nepal showed an intervention that promoted livestock introduction and related training for community development and poverty alleviation was associated with significantly improved child anthropometry and child health. This project involved various non-governmental organisations (NGOs) that independently collected data on the effectiveness of a government driven implementation. The activities represent a viable 'nutrition sensitive' intervention, but these impacts take time to manifest and be sustained. The programmes' collective outputs, monitoring and evaluation efforts and knowledge generation were made possible through well-planned methodology, intervention delivery and data collection through an effective collaboration between the participating organisations and the stakeholders. (Miller *et al.*, 2017).

## 3.2. Constraints at the global level

At the **global level**, much of the food security, agriculture and nutrition data is collated and disseminated by the FAO. Data in the domain of health and nutrition, including those relating to maternal and child nutrition indicators, is collected, and disseminated by the WHO and UNICEF. However, the raw data in both these instances come~~s~~ from the individual member states or regions and therefore the quality and richness of the data are typically dependent on the capacity of the individual nations (OECD, 2019).

The **lack of coordination between national and international agencies** sometimes creates gaps between objectives and delivered outcomes. For instance, 50 percent of African national statistics offices perceived that capacity building programmes did not involve sufficient consultation between national and international stakeholders; and over 30 percent of national statistics offices worldwide expressed that the programmes did not meet their needs (PARIS21, 2018b). This data indicates that country ownership of these capacity programmes is modest. Thus, the understanding the motivations, incentives and political dimensions behind capacity delivery for partners and beneficiaries will assist in making these programmes more relevant and sustainable (OECD, 2019)

The FAO Office of Evaluation (OED) with the support of an external team of thematic experts conducted an evaluation of FAO's statistical support. The aim of this evaluation was to provide Members with an assessment of FAO's statistical contribution to agricultural and rural development and food and nutrition security from 2012 to 2018. The Evaluation Team concluded that **FAO's current internal statistical governance did not provide a solid basis for well-coordinated, coherent, or satisfactory statistical work**. This was attributed to weak enforcement of internal governance arrangements and the confusion arising from a profusion of units/divisions conducting statistical activities (including at regional level) over roles and responsibilities, diluting its effectiveness. The need for FAO to better capitalize regional statistical expertise and regularly evaluate its programme resources allocated to statistical activities to ensure its appropriateness for the objectives of the work plan was recommended. The evaluation also identified that the limitation in statistical assistance provided to countries was further exacerbated by FAO's dependence on extra-budgetary resources for statistical capacity-building which creates uncertainty on the sustainability of this capacity-development work. Thus, despite some progress in terms of quality, the statistics produced and disseminated by FAO were deemed to be only partly compliant with its Statistics Quality Assurance Framework (SQAF). The Evaluation Team further recommended that FAO expediate its efforts to improve the quality of its data and IT infrastructure support and organize and enforce an integrated statistical quality management system to ensure compliance with current and new internationally accepted statistical standards and norms for all its activities (FAO, 2020b).

Furthermore, the lack of a shared vision and accepted consensus among countries on the importance of collecting the data, resistance to harmonization of the indicators and data collection methodology hinders international comparisons. For instance, current global assessment of food consumption and diet quality has no single, validated composite index to measure the multiple dimensions of diet quality across all countries (SOFI, 2020). Global cross-comparison of broad environmental impact of diets is severely hampered by the lack of availability of land, energy, and water use data (SOFI, 2020). The newer domains of food security such as agency also have no broadly agreed upon indicators. Similarly, there is no single, harmonized methodology available for collecting and generating data on the causes and impacts of natural disasters on the agricultural sector. Procedures relating to method of data collection, monitoring and reporting of these impacts at the local, regional and national levels need improvement and harmonisation across countries, to aid better sustainable development planning (FAO, 2017a). Some of the global constraints are reinforced by the lack of coordination between the large number of stakeholders involved and a lack of clear mechanisms of reporting and the means to deliver on the commitments.

Exemplars in achieving success in international collaborations are characterised by the commitment to engaging stakeholders, creating of a shared vision amongst them (NAF Nansen programme) and coordination among all the participating organisations (Nepal's nutrition sensitive livestock introduction programme). See Box 5 on page 17.

### 3.3. Lack of data processing and analytical capabilities

Previous sections in this report have documented the sizable increase in availability of data and information on agriculture, food, and nutrition that has occurred over the last two decades, while highlighting remaining gaps, constraints, and risks that often still prevent food security and nutrition policies throughout the world from being based on fully transparent, reliable, relevant evidence. In this section, we focus on one such constraint~~s~~ in particular; namely: the lack of a broadly diffused, sufficiently sophisticated, **analytic capacity** needed to make sense of such a large amount of available data and information. The problem is a general one, certainly not limited to the fields of agriculture, food security and nutrition, though it appears to be particularly relevant for food security assessments. Apart from the importance of **having a clear framework** to guide the collection of relevant data and their analysis, discussed earlier in this report, the attention in this chapter is devoted to the more technical issue of **ensuring the correct interpretation of the information contained in the data collected**. Common problems encountered when reviewing documents and reports on the evidence used for food security policy making include, for example, (a) limited attention paid to the "noise" that pollutes the variables used and to the extent of residual uncertainty that characterizes the assessments; (b) scarce emphasis on issues of representativeness and on potential selection bias induced in the results when using data collected via population surveys; (c) frequent reference to generic "proxy" variables to compensate for the lack of direct evidence on key aspects of the phenomena under scrutiny; (d) use of composite indexes obtained by aggregating variables in ways that do not follow proper information processing principles; (e) abuse of the concept of measurement, with limited attention given to precise, operational definitions of the variables and statistics used in the quantitative assessments; (f) reference to models that remain "black boxes" for most readers/users. The nature of these problems, associated with the frequency in which they are encountered – particularly within food security assessment and analysis reports, including some published by international organizations and by reputable institutions based in countries where resources available for training and education in statistical analyses cannot be considered a limiting factor – reveals the overall **scarcity of a minimally sufficient, statistical and quantitative analytic literacy**, needed to ensure the validity of the results presented and their proper use.

This is a problem of growing concern, given the repeated calls for policy making being based on evidence that is "rigorous" and "scientific". Certainly, to derive objective conclusions form the analysis of often very scattered, partial, and noisy data, is not an easy task. Similarly, to communicate properly on the sophistication of the analytic approach used, or on the extent of residual uncertainty that surrounds the conclusions derived from existing data, is not simple and may be perceived as not convenient. However, the difficulties are not valid excuses for sweeping the inconvenient truth of a possibly insufficient amount of evidence to make informed decisions, under the carpet of simple statements regarding the "rigour" of analyses. Often, people tend to attribute certainty and objectivity to numbers, just because they are numbers, particularly if published by respectable institutions and when data and analyses are presented as "objective", "neutral" or "scientific". But this, at times, appears to be a rhetoric that won't resist to careful, competent scrutiny. Analyses that make use of sophisticated quantitative models – such as based on regressions, computable general equilibrium models, artificial intelligence, machine learning, etc., – are particularly prone to misinterpretation, given that a full comprehension of the nature and implications of the assumptions made to build the models is likely to remain beyond grasping for most of the intended readers and users of such data and modelled results, including policy makers.

To show the kind of misinterpretations that could derive, in the following subsections of this chapter we shall address each of the problems listed above, with examples drawn from existing food security and nutrition reports, with the objective of distilling useful recommendations directed to both data producers and to data users, that may contribute to make more effective use of the data for food security and nutrition policy making.

"Good-quality data are discrete and intelligible (each datum is individual, separate and separable, and clearly defined), aggregative (can be built into sets), have associated metadata (data about data), and can be linked to other datasets to provide insights not available from a single dataset" (Rosenberg, 2013 as cited in Kitchin, 2021)

### 3.3.1. The importance of recognizing the presence of "noise" in the data

Examples: Reports mentioning the number of people estimated to be in a certain condition (undernourishment, food insecurity, malnutrition), where these are reported as point estimates but are not associated with margins of uncertainty or confidence intervals. The residual uncertainty in the assessment may have important implications for decision making, depending on the objective that data user have.

Discussion:

Recommendations: Ideally, statistics derived from any kind of inferential process should always be accompanied by statements on the level of precision (through margins of error, confidence intervals, etc.). At a minimum, a discussion on how precise any such assessment is expected to be, given the nature of the data and the analytic approach used should be included in the report. If models are used to obtain inference when using variables affected by measurement error, the models should be properly referenced.

### 3.3.2. Representativeness of sample-based inference

Examples: Population statistics derived from sample surveys presented without proper description of the sampling design, including the sampling frame and the modality used to select the sampled units, and of the actions taken to expand to results from the sample to the intended population. This is a problem of growing concern ~~now that~~, more and more, remote data collection is being used via telephone or the internet.

Discussion:

Recommendations: Results derived from the analysis of data collected on samples should always be accompanied by a discussion on the potential statistical bias induced by the sampling design and procedure. Any attempt made at correcting such bias should be properly documented.

### 3.3.3. The use of proxy variable and the elusiveness of "gold standards"

Examples:

Discussion

Recommendations:

### 3.3.4. Combining information or hiding information? The use of composite indexes

Examples:

Discussion:

Recommendations:

### 3.3.5. What do we mean when we say we "measure" something?

Examples:

Discussion:

Recommendations:

### 3.3.6. The "black box" issue

Examples:

Discussion:

Recommendations:

## 4. NEW AND EMERGING DATA-DRIVEN TECHNOLOGIES

Arguably, one of the most impressive and rapid developments in our societies of the last few decades has to do with what has been described as a "data revolution" (Kitchin, 2014). A series of innovations that affect the way in which data are produced, managed, analysed, stored, and utilized is dramatically changing the very nature of data and information. As eloquently put by Kitchin (2014), from being something "time-consuming and costly to generate, analyse and interpret", with the consequence that "good-quality data were a valuable commodity, either jealously guarded or expensively traded", nowadays "the production of data is increasingly becoming a deluge; a wide, deep torrent of timely, varied, resolute and relational data that are relatively low in cost and, outside of business, increasingly open and accessible".

Navigating this torrent presents challenges and opportunities, but it is unavoidable, including for agriculture, food security and nutrition. To help in the endeavour, this chapter discusses the implications of the data revolution on food security and nutrition by first identifying various new and emerging technologies, that produce data and also transform data into information that are especially relevant to food security and nutrition. Subsequently, it situates those data-driven technologies within the FSN data value chain/data lifecycle introduced chapter 1. Then, it discusses their relevance to the different FSN dimensions. Finally, it comments on the associated risks, suggesting appropriate mitigation measures.

## 4.1. New technologies producing and processing data relevant to FSN

### 4.1.1. Producing and collecting data

#### Sensors and Internet of Things (IoT)

A sensor is a device that measures a physical or chemical feature. Sensors include but are not limited to: standard sensors (such as for soil moisture or for tracking animals), weather stations, and remote sensing (e.g., via satellites). Digital images or video (RGB or hyperspectral) are increasingly used to capture reality. These sensors can be fixed or mobile (on tractors, robots, drones, etc). The development of nano-computers (e.g., Raspberry) and microcontrollers (e.g. Arduino) has facilitated and popularised the use of these sensors, making them accessible to a wide population. Sensors are commonly used in IoT applications.

IoT refers to the network of physical objects, which have sensors, software, and other technologies to connect and exchange data with other devices and systems over the Internet. IoT is especially appropriate for automating and monitoring of processes. For instance: livestock management, field observation, quality control, inventory monitoring, etc. IoT is often used together with other technologies such as machine learning, analytics, computer vision and robotics.

In the context of sensors, it is additionally important to point out the concepts of crowdsensing and personal sensing. Crowdsensing (or community sensing) is a paradigm in which a community leverages devices with sensing and computing capabilities to collectively share data and extract information to measure and map phenomena of common interest (Kraft *et al.*, 2020). As for personal sensing, the phenomena that are monitored belong to an individual user. Crowdsensing is considered to apply to scenarios where the phenomena of interest cannot be easily measured by a single user or device (Ganti, Ye and Lei, 2011).

#### Crowdsourcing

Crowdsourcing is the practice of engaging a group of people (i.e., "crowd"), usually via the Internet, to assist in collecting information, ideas, opinions, or other type of task for a common goal such as problem solving, innovation, etc.

### 4.1.2. Transforming data into information

#### Artificial Intelligence, analytics & information visualization

Artificial Intelligence (AI) is the theory and development of computer systems able to carry out tasks commonly associated with human intelligence. AI includes specific fields such as machine learning, perception, robotics, and natural language processing.

Computer vision and deep learning can be used to support visual perception. It has therefore become possible to develop applications for detection, recognition and identification of weeds, pests, plant diseases, and other types of species and objects. The same technologies can be useful for identifying processes such as growth and ripening, and for controlling quality and safety of products. Moreover, the foregoing technologies can be combined with the use of satellite technology and sensors to monitor phenomena that are of specific relevance for food security, such as biodiversity, natural resource use (e.g., land, water, forests, fish banks, etc.), crop production, the climate, etc.

Information visualization is the process of transforming otherwise abstract data into an interactive, visual form that enables or triggers users to use their mental and visual capabilities thereby gaining insight and understanding of that data.

Machine learning, analytics and information visualization have been used for purposes such as: market and price analysis (for instance to predict consumer demand, buying behaviour, consumer perception e.g., sentiment analysis), prediction of crop yield or animal production (for instance, where the inputs are: equipment requirements, and nutrients, and fertilizers), irrigation requirements (for instance, where the inputs are: soil moisture data, precipitation data, evaporation data, and weather forecasts). Such data can also be combined with other data sources (such as FSN processors, distributors, lenders, insurers, etc) and consequently generate recommendations or advice.

Machine learning, analytics and information visualization can also be used to generate personalized nutritional recommendations, track adherence with dietary regimen, and generate reminders.

One of the natural language processing systems that is relevant to FSN is Interactive Voice Response (IVR). IVR is a technology that allows humans to interact with a computer-operated phone system using voice and dual-tone multi-frequency (DTMF) user interface, allowing them to provide and/or access information. IVR can be used to support, complement, and enhance the conventional FSN phone-based interviews and household/individual surveys. It can also be used to offer customer services e.g., agricultural extension services.

Robots, drones, and autonomous vehicles are being used in agriculture and food processing for tasks such as: automated and precision watering, sowing, spraying, harvesting, etc (Santos Valle and Kienzle, 2020). It is worth noting that these machines rely on technologies such as machine learning, computer vision and the Internet of Things (IoT). They are also a new potential source of data.

### Semantic web

Semantic web technologies enable the creation of web-based data stores, the construction of vocabularies and ontologies, and the writing of rules to process the data. At the top of the Semantic web stack is inference, which is reasoning about data using rules. The use of shared vocabularies and ontologies could ensure semantic interoperability between datasets of diverse origins.

### Online social media

Social media refers to user generated information, opinions, video, audio, and multimedia that are shared and discussed over digital networks. Online social media is useful in agriculture and nutrition. For instance: for agricultural extension and advisory services, studying dietary choices and nutritional challenges.

### Blockchain technology

Blockchain technology (or Distributed Ledger Technology) is being used to support transparency, trust, certification, and traceability. For instance, in food supply chains and land registration (FAO, 2020a; Sylvester, 2019).

Blockchain technology, smart contracts, statistics, and machine learning can also address trust and credibility, for instance in research.

### Virtual Reality and Augmented Reality

Virtual Reality (VR) is a computer-generated simulated environment with objects and scenes that seem real, making the user feel immersed in their surroundings. Augmented reality (AR) is an interactive experience of a real-world environment where the objects in the real world are enhanced by computer-generated information and features. VR and AR can be used for purposes such as: repairing agricultural equipment, conducting virtual agricultural tours, visualizing agricultural fields, conducting training, etc.

#### Digital twin

A digital twin is a virtual representation that serves as the real-time digital counterpart of a physical object or system and that helps in decision-making. Digital twins can be used to monitor, analyse, and report about food security and nutrition systems and the environment. They can also support a continuous stream of automated operations (see e.g., Portela *et al.*, 2021).

### 4.1.3. Processing data

#### Big data and cloud computing

Big data refers to high-volume, high-velocity, high-variety and/or high-veracity information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation. For instance: CGIAR's Platform for Big Data in Agriculture (https://bigdata.cgiar.org/); Data for Oceanographic Learning & Fisheries Intelligence Needs (DOLFIN) (https://fisheries.groupcls.com/fishermen/fisheries-intelligence/); etc.

Cloud computing centralizes resources and services remotely and facilitates their use by multiple users without the need for the users to store the resources or install the services on their individual hard drives.

#### Ubiquitous Computing

Ubiquitous computing is a concept where computing is made to appear or occur anytime and everywhere. Ubiquitous computing has become widespread especially through mobile computing, where end-users carry their device (such as a mobile phone) and use it in everyday activities and contexts. Respondents can be contacted through Short Message Service (SMS), Unstructured Supplementary Service Data (USSD), chatbots, Computer-Assisted Telephone Interviewing (CATI), and other data-collection applications (for instance ODK-based technologies such as CommCare, TaroWorks, etc). It is also possible for some of the end-user devices to support passive collection of data. For instance: usage data (such as airtime credit or Internet bundles used) and device sensor-based data (such as GPS location and user movement). Moreover, some of the devices can be used by users to run other kinds of data-driven applications.

#### System integration and aggregation

Different systems can be brought together so that they connect or link to each other, share and/or exchange data or information (for instance through Application Programming Interfaces (APIs)). Consequently, it is possible that systems can gather data from other systems (i.e., other data sources) and perform various operations on these data from multiple data sources for instance: data fusion, analysis, summarizing, etc.

## 4.2. New data-driven technologies and the FSN data value chain

Digital technologies are relevant to the FSN data value chain/data lifecycle which was introduced and described in Chapter 1.

Regarding defining evidence priorities and questions, digital technologies can be used to assess options, and propose priorities and questions.

Digital technologies can support the review, consolidation, collection, curation, and analysis of data in various ways. For instance:

- Supporting the production and collection of data.

- Linking, integrating, and enriching data from different sources.
- Enabling respondents to assist in cleaning up data.
- Supporting aggregation of data.
- Supporting validation, verification, and authentication of data.
- Support detection of errors in data.
- Analyzing and predicting food production; food supplies, food aid and food stock levels; dynamics of net trade; occurrence of adverse conditions; feeding practices; markets and prices.

As for translating and disseminating results and conclusions, digital technologies can be used, for instance to:

- Make data available and accessible.
- Aid the presentation of data to users by rendering it easy to understand.
- Support efficient communication and wide distribution of data.

Digital technologies can support users to engage and use results and conclusions to make decisions. For instance: digital twins can be used to profile food security and nutrition entities (e.g., equipment, animals, and crops) and relevant people (e.g., subjects such as farmers, buyers, etc.) and the resultant data can consequently be used to gain insights for decision making.

The relevance of digital technologies to the FSN data value chain, including specific digital technologies and examples of existing initiatives, is further described and illustrated in Table 2.

## Table 2 Relevant data-driven new digital technologies by element in the data cycle

**A) Define evidence priorities and questions**

| Relevant Data-driven Technologies | Relevance of Data-driven Technologies | Examples of Initiatives and References |
|---|---|---|
| Machine Learning (and Artificial Intelligence in general) | Assessing options and proposing priorities and questions | (Di Vaio *et al.*, 2020) |

**B) Review, consolidate, collect, curate, and analyse data**

| Relevant Data-driven Technologies | Relevance of Data-driven Technologies | Examples of Initiatives and References |
|---|---|---|
| Visual perception technologies together with robotics, IoT, GIS, satellite technologies and digital twins. | Collecting data about agricultural fields, weeds, pests, diseases, and other natural food resources (e.g., wild foods). | GIEWS (Global Information and Early Warning System) (https://www.fao.org/giews/en/)<br>WFP's DataWiz (https://dataviz.vam.wfp.org/)<br>IFPRI Food Security Portal (https://www.foodsecurityportal.org/)<br>Crop Monitor Early Warning; etc. |
| Crowdsourcing, crowd sensing, online social media, SMS, USSD, chatbots, ODK-based technologies, IVR and other forms of mobile applications. | Supporting data production and collection with the respondents as users. | INDDEX24 Mobile App (https://inddex.nutrition.tufts.edu/inddex24-mobile-app)<br>mKisan (https://mkisan.gov.in),<br>etc. |
| Semantic web | Linking and integrating data from different sources. | FAO's AGROVOC (https://agrovoc.fao.org/);<br>AgroPortal (http://agroportal.lirmm.fr/);<br>Crop Ontology (https://cropontology.org/); etc |

| | | |
|---|---|---|
| Digital twin | Digital twins Integrating and enriching data coming from several heterogeneous sources. | Wageningen University & Research's Digital Twin projects (Virtual tomato crops; Me, my diet and I; and Digital Future Farm) (https://www.wur.nl/en/newsarticle/WUR-is-working-on-Digital-Twins-for-tomatoes-food-and-farming.htm ) |
| Crowdsourcing, crowd sensing, online social media, other forms of mobile applications and IVR | Enabling respondents to assist in cleaning up data. | https://forestsnews.cifor.org/71914/crowd-sourced-but-from-whom-profiling-citizen-scientists-in-a-kenyan-water-monitoring-project?fnl=en |
| Big data | Supporting aggregation of data. | CGIAR Platform for Big Data in Agriculture (https://bigdata.cgiar.org/) |
| Machine learning, analytics, information visualization, big data | Revisiting and verifying standard statistics e.g., to detect errors. | AmeriFlux (https://ameriflux.lbl.gov/) |
| Blockchain technology | Authentication of FSN data. | (Cui *et al.*, 2020)<br>(Iftekhar, Cui and Yang, 2021)<br>(Xu *et al.*, 2020) |
| Machine learning and analytics | Analysing and predicting: food production; food supplies, food aid and food stock levels; dynamics of net trade; occurrence of adverse conditions; feeding practices; markets and prices. | WFP's HungerMap (https://hungermap.wfp.org/)<br>International Research Institute for Climate and Society (https://iri.columbia.edu/)<br>**FAO**STAT (https://www.fao.org/faostat/en/)<br>GIEWS (https://www.fao.org/giews/en/)<br>IPC Mapping Tool;<br>(Fernandes *et al.*, 2015) |

**C) Translate and disseminate results and conclusions**

| **Relevant Data-driven Technologies** | **Relevance of Data-driven Technologies** | **Examples of Initiatives and References** |
|---|---|---|
| Information visualization | Aiding the presentation of data to users by rendering it easy to understand. | FAOSTAT; The Food Systems Dashboard; INDDEX Project; ICES Marine Food Stock Assessment Database; etc. |

| | | |
|---|---|---|
| Big data and cloud computing | Making data available and accessible. | FAOSTAT; INFOODS; IPC Mapping Tool; The Food Systems Dashboard; INDDEX Project; etc. |
| Social media | Efficient communication and wide distribution of data. | Monitoring with social media: Experiences from "integrating" WhatsApp in the M&E system under sweet potato value chain (https://www.degruyter.com/document/doi/10.1515/opag-2020-0045/html); etc |
| Semantic web | Enhancing access to and understandability of data. | FAO's AGROVOC (https://agrovoc.fao.org/); AgroPortal (http://agroportal.lirmm.fr/); Crop Ontology (https://cropontology.org/); etc |

**D) Engage and use results and conclusions to make decisions**

| **Relevant Data-driven Technologies** | **Relevance of Data-driven Technologies** | **Examples of Initiatives and References** |
|---|---|---|
| Digital twin and AI | Profiling food security and nutrition entities (e.g., equipment, animals and crops) and relevant people (e.g., subjects such as farmers, buyers, etc), and consequently using the data generated to gain insights for decision making. | IBM Watson platform<br>Digital Twin Ocean project (https://www.cls.fr/en/digital-twin-ocean-identifying-marine-heatwaves-with-artificial-intelligence/) |

## 4.3. How the various dimensions of FSN can be supported by new data-driven technologies support

Digital technologies can support the various dimensions of FSN in many ways.

Regarding the **availability** dimension, digital technologies can be used:

- To map and monitor agricultural fields and other natural food resources (e.g., wild foods and fisheries resources).
- To detect elements that may positively or negatively affect food production (e.g., pests, diseases, and weeds).
- By respondents e.g., by farmers, veterinary officers, and agricultural extension officers to report and monitor the presence of pests and diseases.
- To determine, monitor or predict: food supplies, food aid; food stock levels; dynamics of net trade.

As for the **access** dimension, digital technologies can be used:

- To analyze and predict markets and prices.
- To map and monitor physical transport and communication infrastructure.
- By respondents, to report incomes/expenditures, prices, and status of physical transport and communication infrastructure.

As far as the **utilization** dimension is concerned, digital technologies can be used in several ways:

- They can be used by respondents to questionnaires to report on feeding practices, food preparation, food safety, dietary diversity, health seeking behaviour.
- They can be used to determine, monitor, or predict feeding practices.
- They can be used to track, trace and report about food products and stocks that are unsafe or otherwise.
- They can be used to profile relevant objects (such as agricultural equipment, crops, animals, etc.) and respondents (such as farmers, buyers, etc.) and the data generated can consequently be used to track relevant food security and nutrition indicators.

As for the **stability** dimension, possible applications of digital technologies include:

- Mapping and monitoring incidents and natural events.
- Detecting, monitoring, or predicting occurrence of adverse conditions.
- Monitoring and reporting relevant events/incidents and mapping hotspots.

Digital technologies can support the **agency** dimension in various ways. For instance:

- Providing users with access to information that can guide them in making their own decisions.
- Enabling users to report incidences of concern (e.g., mistreatment).
- Supporting users to engage in policy processes.
- Promotion of transparency and accountability.
- Supporting the authentication of agency-related information. For instance, ownership of agricultural resources (such as land).
- Monitoring or predicting the occurrence of factors such as: gender inequalities, wealth and income disparities, uneven access to ICT, uneven resource distribution, etc.

As for the **sustainability** dimension, digital technologies can be used for instance to:

- Monitor the environment, weather, agricultural fields, and other natural resources.

- Determine, monitor, or predict elements that may negatively or positively affect the environment and climate.
- Report activities and events that may negatively or positively affect the environment and climate.

The relevance of digital technologies to the FSN dimensions, including specific digital technologies and examples of efforts, is further described and illustrated in Table 3.

## Table 3 Relevance of data-driven new technologies to the various FSN Dimensions

**Availability**

| Technology | Relevance | Examples of Efforts |
|---|---|---|
| AI, IoT, GIS, satellite technologies and digital twins | Mapping and monitoring agricultural fields and other natural food resources (e.g., wild foods and fisheries resources).<br><br>Detecting elements that may positively or negatively affect food production (e.g., pests, diseases, and weeds). | Crop Monitor for AMIS;<br><br>FAOSTAT;<br><br>PlantVillage Nuru (https://bigdata.cgiar.org/divi_overlay/plantvillage-nuru/); |
| IVR, CATI, crowdsourcing, crowd sensing, online social media, SMS, USSD, chatbots, ODK-based technologies and other forms of mobile applications. | Supporting respondents (e.g., farmers, veterinary officers, and agricultural extension officers) to report and monitor the presence of pests and diseases. | PlantVillage Nuru; (https://plantvillage.psu.edu/projects)<br><br>mKisan (https://mkisan.gov.in)<br><br>Monitoring with social media: Experiences from "integrating" WhatsApp in the M&E system under sweet potato value chain (https://www.degruyter.com/document/doi/10.1515/opag-2020-0045/html); etc |
| Machine learning, big data, semantic web, cloud computing, analytics and information visualization | Determining, monitoring or predicting: food supplies, food aid; food stock levels; dynamics of net trade. | GIEWS; FAOSTAT; ICES Marine Food Stock Assessment Database;<br><br>(Fernandes *et al.*, 2015)<br><br>etc. |

**Access**

| Technology | Relevance | Examples of Efforts |
|---|---|---|
| Machine learning, big data, and analytics | Analyzing and predicting markets and prices. | GIEWS; FAOSTAT; etc. |

| | | |
|---|---|---|
| Visual perception technologies together with robotics, IoT, GIS, satellite technologies and digital twins | Mapping and monitoring physical transport and communication infrastructure. | (Kamilaris and Pitsillides, 2014)<br>(Du *et al.*, 2015) |
| Crowdsourcing, crowd sensing, online social media, mobile computing, IVR | Supporting respondents to report: incomes/expenditures, prices, and status of physical transport and communication infrastructure. | Report on a study to crowdsource farmgate prices for maize and soybeans in Malawi (https://www.ifpri.org/publication/report-study-crowdsource-farmgate-prices-maize-and-soybeans-malawi ) |

**Utilization**

| Technology | Relevance | Examples of Efforts |
|---|---|---|
| Crowdsourcing, crowd sensing, online social media, mobile computing and IVR | Supporting respondents to report: feeding practices, food preparation, food safety, dietary diversity, health seeking behaviour. | (Turner-McGrievy *et al.*, 2015) |
| Machine learning, analytics, semantic web, and information visualization | Determining, monitoring, or predicting feeding practices. | INFOODS ( https://www.fao.org/infoods/infoods/en/)<br>WFP's HungerMap (https://hungermap.wfp.org/)<br>etc. |
| Blockchain technology | Tracking, tracing and reporting about food products and stocks that are unsafe or otherwise. | |
| Digital twin | Profiling relevant objects (such as agricultural equipment, crops, animals, etc) and respondents (such as farmers, buyers, etc), and consequently using the data generated to track relevant food security and nutrition indicators. | Wageningen University & Research's Digital Twin projects (Virtual tomato crops; Me, my diet and I; and Digital Future Farm) https://www.wur.nl/en/newsarticle/WUR-is-working-on-Digital-Twins-for-tomatoes-food-and-farming.htm |

**Stability**

| Technology | Relevance | Examples of Efforts |
| --- | --- | --- |
| Visual perception technologies together with robotics, IoT, GIS and satellite technologies | Mapping and monitoring incidents and natural events. | WFP's DataWiz (https://dataviz.vam.wfp.org/)<br>(Du *et al.*, 2015)<br>etc. |
| Machine learning, big data, semantic web, cloud computing, system integration & aggregation, analytics and information visualization | Determining, monitoring, or predicting occurrence of adverse conditions. | FAOSTAT (https://www.fao.org/faostat/en)<br>GIEWS (https://www.fao.org/giews/en/)<br>IPC Mapping Tool (https://www.ipcinfo.org/ipc-country-analysis/ipc-mapping-tool/)<br>etc |
| Crowdsourcing, crowd sensing, online social media, mobile computing, IVR | Monitoring and reporting relevant events/incidents and mapping hotspots. | (Okolloh, 2009) |

**Agency**

| Technology | Relevance | Examples of Efforts |
| --- | --- | --- |
| Blockchain technology | Supporting the authentication of agency-related information. For instance, ownership of agricultural resources (such as land). | (Shang and Price, 2019)<br>etc |
| Big data, machine learning, semantic web, visualization, online social media, and mobile computing | Enabling users to access information that can guide them in making their own decisions. | MyCrop (http://www.mycrop.com ) |

| | | |
|---|---|---|
| Crowdsourcing, crowd sensing, online social media, mobile computing, IVR | Enabling users to report incidences of concern (e.g., mistreatment), to engage in policy processes.<br><br>Promotion of transparency and accountability.<br><br>Supporting the (ethical) monitoring of individuals/community digitally (e.g., sentiment analysis). | Harassmap (https://www.harassmap.com );<br><br>Ushahidi (https://www.ushahidi.com/) |
| Machine learning, big data, analytics and information visualization | Determining, monitoring or predicting the occurrence of factors such as: gender inequalities, wealth and income disparities, uneven access to ICT, uneven resource distribution, etc. | Visualize Gender Equality project (https://opfistula.org/visualize-gender-equality) |

**Sustainability**

| Technology | Relevance | Examples of Efforts |
|---|---|---|
| Visual perception technologies together with robotics, IoT, GIS, satellite technologies and digital twins | Monitoring the environment, weather, agricultural fields, and other natural resources. | International Research Institute for Climate and Society (IRI) (https://iri.columbia.edu/)<br><br>etc. |
| Machine learning, big data, semantic web, cloud computing, system integration & aggregation, analytics and information visualization | Determining, monitoring or predicting elements that may negatively or positively affect the environment and climate. | FAOSTAT (https://www.fao.org/faostat/en);<br><br>etc. |
| Crowdsourcing, crowd sensing, online social media, mobile computing, IVR | Reporting activities and events that may negatively or positively affect the environment and climate. | Climate CoLab (https://www.climatecolab.org);<br><br>sickweather app (https://www.sickweather.com);<br><br>350 (https://350.org)<br><br>(Jeff Biggar, 2010) |

## 4.4. Risks inherent in the use of data-driven technologies for FSN

### 4.4.1. Ethical and data security issues

There are various ethical concerns associated with digital technologies. Digital technologies can be used to undertake tasks in a manner that undermines or overrides autonomous rational choice. While this may ultimately be beneficial in some situations (e.g., to avert disaster), there are scenarios where this may be used maliciously. For instance:

- There are situations where inconsiderate digital automation may create conflict with norms such as human rights and justice.
- There are situations where digital technologies can be used to negatively manipulate user behaviour in a way that undermines autonomous rational choice. Users' intense interaction with digital technologies enables the latter to gain much knowledge about the users. Notwithstanding the potential benefits of acquiring and using such knowledge, algorithms can be used to target users with just the kind of interaction to influence them negatively. This manipulation often uses "dark patterns", whereby where user interface design choices coerce, steer, or deceive users into making decisions that, if fully informed and capable of opting for alternatives, they might not make.

Another pertinent concern relating to data-driven technologies for food security and nutrition is who owns the FSN data and who has control over its use and implementation. Moreover, users and respondents are concerned about the privacy, security and protection of their data. For instance, that their data may end up in the wrong hands, be used against them, be used to exploit them, or put them in precarious positions in the future. This can also lead the risk of agro-food market dominance by few monopolies that have control or ownership of data.

### 4.4.2. Trust and transparency issues

Technologies such as machine learning can facilitate automatic decision-making. If the decision-making process is hidden from the person directly affected by the outcomes, then the underlying technologies can raise trust issues. This is why research for an explainable Artificial Intelligence (xAI) is developing (e.g., Rudin, 2019)

### 4.4.3. Quality of data

Data quality entails elements such as: accuracy, completeness, timeliness, validity, consistency, etc. Data collection from users or respondents through technologies such as online social media, crowdsourcing and other mobile computing-based devices is relatively subjective and therefore subject to factors such as deception and carelessness. It has also been reported that data collected from citizen science efforts tends to be noisy and variable (Kelling *et al.*, 2015). Moreover, there might be distractions in the respondents' uncontrolled settings. The data collected may therefore suffer from poor quality. Machine learning algorithms can give inaccurate recommendations (for instance due to inaccurate data). IoT and sensors can give false or misleading readings (for instance due to environmental complexities). The result may be detrimental agricultural and nutritional decisions and actions.

### 4.4.4. Insufficient capacity and inequities

Data-driven technologies involve relatively high investment costs. The technologies are being mainly used by organizations and farmers who can afford (for instance, in large industrial farms (Carbonell, 2016 pp- 1-13). The technologies are relatively expensive for other organizations and the poorer farmers with small farms. The latter might also not have the capacity to use the technologies or interpret data results. Such scenarios are likely to lead to inequalities (such as digital divide).

Moreover, some organizations that carry out data collection and analysis are finding the cost of requisite technological infrastructure prohibitive. They are also finding themselves not having enough personnel with skills in core data competencies (e.g. data analysis, information visualization, interpretation and decision making).

### 4.4.5. E-waste

Data-driven technologies in agriculture and nutrition may involve usage of electronic equipment such as: IoT infrastructure and devices, laptops, computer networking infrastructure and appliances, mobile phones, servers, etc. Such equipment has toxic components that are dangerous to human health (such as mercury, lead, cadmium, barium, and lithium). Activities such as repair, disposal, and recycling should therefore be carried out in an environment-friendly and safe manner.

### 4.4.6. Energy consumption and emissions

Some of the equipment that comprise the infrastructure of data-driven technologies are electrically powered. For instance: servers, storage drives, network devices, etc. Data-driven technologies relating to blockchain technology, cloud computing, big data, machine learning, visual perception (such as through deep learning) are particularly energy-intensive. The implementation and deployment of data-driven technologies will therefore often imply more energy consumption and emissions. Higher energy consumption incurs more financial costs and raises environmental challenges. It is also worth noting that these technologies are increasingly permeating and being deployed in habitations of human and other living things (such as animals and plants).

### 4.4.7. Interoperability of data

Poor (and in some instances lack of) interoperability of disparate sets of food security and nutrition data is an area of concern. Interoperability makes it possible for different systems to share, exchange and understand data. Interoperability of data is therefore also critical when efforts are being made to integrate different systems. Integration is key toward making data-driven technologies and systems to be widely useful. It is gratifying to note that interoperability efforts, such as FAO's AGROVOC, are steps in the right direction.

## 4.5. Mitigating the risks inherent in the use of data-driven technologies for FSN

### 4.5.1. Ethical frameworks, legislation, and policies

It is important to formulate and enact laws, regulations and policies on ethics, consent, privacy, data protection, privacy, ownership, fair competition, and copyright. Digital technologies that are transparent and give users freedom of choice are desirable. It is valuable to build the capacity of users. For instance: providing users with information; educating users about their digital rights and responsibilities; ensuring that users are trained or supported to handle relevant technologies; creating an enabling environment for users to access the required digital infrastructure and digital resources; etc.

Examples of data protection and privacy laws and regulations include: the European Union's General Data Protection Regulation (https://gdpr-info.eu/), UK's Data Protection Act (https://www.legislation.gov.uk/ukpga/2018/12/contents/enacted). Such laws and regulations are often subject to the oversight of an independent authority to ensure compliance and protection of individuals' rights. "At a broader level, the UN Global Pulse has developed a set of Privacy Principles in consultation with experts from public and private sector, academia and civil society. The United Nations Secretary-General's Independent Expert Advisory Group on a Data Revolution for Sustainable Development has recommended to develop a global consensus on principles and standards concerning legal, technical, privacy, geospatial and statistical standards which, among other things, will facilitate openness and information exchange and promote and protect human rights."(FAO, 2017b; UN, 2015).

It is also important to formulate and enact laws and regulations on e-waste. For instance, in 2012, the European Parliament passed an update of the 2003 Waste Electrical and Electronic Equipment (WEEE) Directive to curb dumping of electronic goods. In March 2020, the European Commission said it would introduce new waste reduction targets and sustainability laws to ensure that products placed on the EU market are recyclable, repairable, and designed to last longer. (Marine Strauss, 2020)

### 4.5.2. Involvement of and collaboration with diverse stakeholders

Early and continuous involvement of all relevant stakeholders is required for the acceptance and success of new technologies in the FSN sector. Stakeholders include, but are not limited to: farmers, governments, industry, consumer groups and non-government organizations. For instance, although upstream and downstream sectors influence the adoption of technologies by farmers, they can learn from farmers so that technologies implemented take into account the requirements of the farmers (OECD, 2001).

Collaboration too is key for the success of digital technologies in FSN. Its benefits include but are not limited to:

- Ensuring interoperability of technology standards and architectures (such as in the implementation and use of blockchain technology).
- Pooling digital resources (such as digital infrastructure, data, etc).
- Sharing best practices and mutually beneficial information.
- Developing context-relevant and user-relevant technological interventions

Technologies should offer services and content that are based on and adapted from trusted sources, and that take into consideration local contexts in order to meet the unique needs and preferences of different user groups (FAO, 2013a).

### 4.5.3. Value chain approach and integration of services

Data-driven technologies should be developed taking into account the food security and nutrition value chain which has many interconnections. Moreover, the service that a specific data-driven technology provides should not be considered in isolation. The service will often need to integrate or interact with other services.

### 4.5.4. Building and enhancing capacity

It is important to Invest in the necessary technology/infrastructure and research. For instance: for data interoperability and data quality; for improving access to & affordability of technology; etc. It is also important to building and enhance human capacity. For instance: training in core data competencies (e.g., data analysis, information visualization, interpretation and decision making); educating users to support the data lifecycle process and to improve data quality; etc. Capacity issues are discussed in more details in Section 4.

Note:

- There are many diverse factors that can limit the extent to which the data-driven technologies are adopted and used. For instance: capacity limitations as described in Section 5. Consequently, the use or the access of these technologies may create discrepancies between countries, agricultural systems, people, etc.
- Conversely, these technologies could lift locks and smooth out differences between countries (e.g., satellite, big data analysis, "e-life" data used by companies for whom data is valuable, such as Google).
- Thanks to these technologies, the Data value chain may exist at different level : from very local one (short cycle sale) to international regulation or policies
- What about agility in the data collection and analysis processes? There is a risk by dealing local and international dimensions, and using high-level conceptual framework, that the collected data would be not so useful, thus how to proceed, which process must be set up at which scale, to first identify weakly used data, 2nd, to identify which such a weak use, 3rd to correct the recommendation on data collection?
- Related to section 5: the abilities of the new generations with the new tech e.g., smartphone (see GSMA data on adoption), could be a leverage and an accelerator that would smooth out some of the differences between countries, etc. In addition, technological leapfrogging could be a leverage.

# 5. Institutions and governance for data collection, analysis, and use

## 5.1. Optimizing the way we generate, use and maintain data

The food sector is highly vulnerable to the rapid and interconnected changes the world is experiencing (demographic trends, economic trends, climate change). Reliable and timely data is essential to improve the quality and effectiveness of policy design and implementation in this rapidly changing environment.

Besides data availability and data quality, good data governance is crucial to address FNS challenges. For this, global and national institutions, as well as individual actors such as academic researchers, NGOs and citizens, have to work together to establish and maintain data systems that can inform the design of interventions and policies needed to address FSN challenges.

Technological innovation opens the door to new data sources and increased data volume but may also divert attention from strengthening data collection procedures, as well as from identifying data governance capabilities and gaps. According to Carletto et al. (2021), “this underscores the need to better exploit complementarities between traditional and alternative data sources and methods, which will require both technical solutions as well as creative institutional arrangements that foster collaboration and value addition”.

Improving FSN data governance involves changing the way in which we generate, use and maintain data. In this section, we discuss FSN data governance issues, with a particular focus on:

- Data governance principles: people, processes, technology
- Data protection: sovereignty, security, data quality, privacy
- Transparency and governance of official statistics
- Data governance mechanisms in a digital world
- Links between conventional and novel data sources
- Global and regional initiatives addressing governance challenges

## 5.2. Transparency and governance of official statistics

The United Nations Statistics Division (UNSD) has a long history guiding the advancement of global statistics. The Fundamental Principles of Official Statistics (Resolution 2014 A/RES/68/261) stress the need to harmonize concepts and methods, to use professional criteria (including scientific methods and ethics) to collect and use data, to develop transparent rules and governance mechanisms and to enhance coordination among statistical agencies.

The growing interest in timely and detailed data, coupled with the emergence of new data producers, has led to an increase in supply and demand for statistical data. National statistical systems around the world need to adapt to meet this increased demand and continue to provide high-quality and trustworthy data. International agreements and governance mechanisms are essential to improve coordination among data providers (i.e. different institutions use different food indicators or provide different values for the same indicator in the same country, product and time) and between data providers and data users (i.e. data systems need to respect confidentiality while ensuring data usability).

Although there are initiatives to coordinate data collection and governance, greater internal and international coordination is needed to avoid the proliferation of disconnected data initiatives that can lead to data gaps and duplication. To support the achievement of the SDGs, the UNSD is intensifying efforts to develop indicators and integrate geospatial and statistical data. However, not all countries have the same capability to establish food data systems capable of collecting disaggregated and detail data over time. Therefore, for these initiatives to succeed, the efforts to modernize national statistical systems needs to be accompanied by assistance to countries with limited capabilities.

### 5.3. Open science, open data

Topics:

- Academic integrity and ethics of data collection, analysis and dissemination
- Usage of official statistics: ensuring confidentiality and privacy of primary data (microdata)
- Open access versus restricted access

"Open science" initiatives are developing rapidly in all research areas, including FNS. The openness of data and research output facilitates timely and universal access to information on food systems developments.

More effort is needed to generate information on nutrition and health effects and monitor progress in nutrition indicators. According to Mozaffarian et al. (2018), academia should prioritise research on optimal dietary targets and cost-effective policies; monitor and evaluate health indicators and policy outcomes; engage with communities, advocacy groups, the media, business, and policy makers; and inform and evaluate government and industry efforts.

### 5.4. New data technologies entail new governance challenges

Topics:

- Ownership of data collected.
- Data privacy and protection.
- Unethical and malicious use of digital technologies (such as: manipulation of users, e-waste, emissions, etc.).
- Emerging concerns on sharing and use of food and nutrition data
- Quality issues: inadequate sampling frames (high rates of non-response and under-coverage of web-based surveys…), high potential of citizen-generated data to fill gaps but need to address flaws in terms of data quality, representativity and potential bias due to self-selection of respondents.
- More data does not automatically mean better information: data analysis.
- How to combine conventional data sources with novel data generation approaches.

The spread of new data sources (satellite data, data from sensors, citizen-generated data, social media data) contributes to impressive improvements in data availability and timeliness and will likely have important implications for FNS. However, more FNS data does not translate automatically in improved data systems. Data governance frameworks need to account for the new challenges posed by data-driven technologies to balance their positive and negative impacts on FNS. An example of positive impact is the higher amount of data available for consumers, helping them to make better decisions. An example of negative impact is the transfer of consumers data to the private corporations that provide the digital technologies, raising concerns about data ownership, data protection and consumers agency.

### 5.5. Review of recent initiatives on data governance for FSN

- Global Strategy to Improve Agricultural and Rural Statistics (see http://gsars.org/en/)
- Living Standards Measurement Study—Integrated Surveys on Agriculture (see https://www.worldbank.org/en/programs/lsms/initiatives/lsms-isa)
- 50 × 2,030 Data Smart Agriculture programme (see https://www.50x2030.org/)
- WDR 2021 dedicated to data:

### 5.6. Moving towards "good FSN data governance"

The development of improved knowledge systems to inform more effective policy action requires to take special attention to governance issues. New institutional arrangements are being promoted in some countries to facilitate the effective integration, sharing and reuse of FSN data. International standards for FNS data governance and data sharing should be developed/enhanced. They are international institutions already well positioned to lead such initiatives and provide country-support.

## 6. Conclusions and recommendations

(to be completed)

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## Glossary

**Agriculture**: when not otherwise specified, the term *agriculture* in this report is meant to include all activities related to crops, livestock, aquaculture, fisheries, and forestry.

**Agri-food system**: it is the set of all public and private activities involved in the production, distribution and consumption of food, including the entire value chain from the production of basic commodities to the distribution of food items to consumers.

(to be completed)