

Is Satellite Data Right for Your Needs?

HUMANITARIAN DECISION-MAKING GUIDE



FOOD SECURITY

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Introduction

Food insecurity and famine remain among the most severe and persistent humanitarian challenges in the world, with conflict serving as a primary driver in many of the most affected areas. In these contexts, Earth observations (EO) can expand monitoring capabilities when traditional ground-based monitoring is impossible or unreliable due to insecurity, disaster, or other access restrictions.

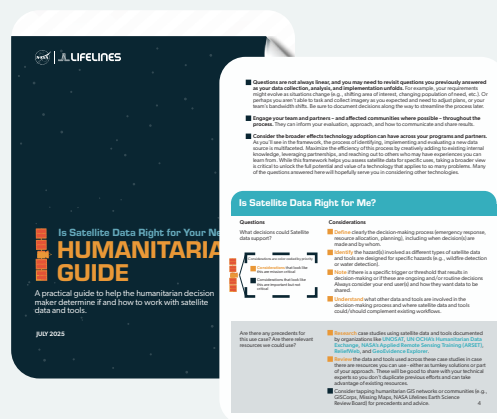
EO data can support multiple forms of analysis, including:

1. **Environmental monitoring** (e.g., agricultural analysis and extreme weather forecasting)
2. **Food systems monitoring** (e.g., analysis of market activity and damage to food infrastructure)
3. **Operational support for emergency food assistance**

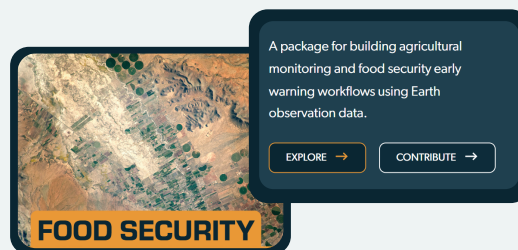
In this way, satellite data can inform a variety of humanitarian decisions, including food security assessments and emergency response.

This case study on food security can ultimately support a range of actors including formal famine review committees, governments and donors, humanitarian organizations, and local responders. This guide offers a framework that practitioners can adapt to their own contexts. It aims to equip humanitarian decision makers with practical tools to anticipate and respond more rapidly and effectively in emergencies.

This case study supplements the **EO Humanitarian Guide**, published by NASA Lifelines in July 2025, and applies the guide's **Suitability Assessment Framework for Satellite Data**. The framework walks through a structured set of questions to help end users determine whether satellite data is fit for purpose, as well as considerations for how to integrate EO data into workflows. This case study is designed for **humanitarian decision makers** who recognize the value of data-driven approaches but may not have deep technical expertise in remote sensing or geospatial analysis.



This case study is accompanied by a companion **Food Security Data Studio Package**, which focuses on environmental monitoring applications. While this report focuses on the analytical and decision-making framework, the Data Studio Package provides hands-on guidance for accessing and working with specific datasets and tools.



Is Satellite Data Right for Me?



This section aims to help decisionmakers determine whether Earth observations could be a good fit for the food security work they intend to support. The questions below walk through what decisions EO could inform, existing precedents, associated ethical and risk considerations, and examples of what specific EO data could support different applications. Working through this section can clarify whether and how EO could add value as a source of evidence.

What decisions could satellite data support?

Figure 1: Satellite-informed decision-making across the food security arc



Earth observations can inform humanitarian understanding of where food insecurity is occurring or may emerge, how severe it is, and over what geographic extent. For local organizations who may already understand the nature of food insecurity in their own communities, EO data can generate rapid, credible evidence without requiring costly ground assessments. This evidence can inform decisions that span the full arc of food security work, from forecasting risks before a crisis emerges to guiding response during an active emergency, as well as evaluating outcomes and documenting harms after the fact. Some of these decisions are included in **Figure 1**.

See the **Decision Scoping Tool in Appendix A** for a set of questions prompting humanitarian to identify geographic or environmental factors within their programs that could benefit from analysis of satellite data.

Are there any precedents for this use case? Are there relevant resources we could use?

EO data has been widely applied to analyze agriculture and food security. Precedents include the following:

Early Warning and Anticipatory Action | NASA, USGS, UCSB Climate Hazards Group, and FEWS NET

The Famine Early Warning Systems Network (FEWS NET)'s Land Data Assimilation System (FLDAS), which integrates satellite precipitation data and other inputs, helped characterize the extent and severity of the 2015–16 Southern Africa drought in support of food and water security assessments and humanitarian relief planning.¹

Food Security Assessment | IPC Famine Review Committee for Sudan

The Integrated Food Security Phase Classification (IPC) is a global initiative to enhance food security and nutrition analysis, and it serves as a leading authority on food security assessments. Under IPC guidelines, remote sensing does not count as direct evidence, which requires direct measurement of key outcomes such as mortality rate and malnutrition prevalence. Still, satellite data related to attacks on civilians and mortality estimates contributed to the IPC-5 (Famine) finding for El-Fasher, Sudan as corroborating indirect evidence.²

Early Warning and Emergency Response | WFP, SERVIR-HKH, and ICIMOD

Earth observation analyses provided by the International Centre for Integrated Mountain Development (ICIMOD) through the SERVIR-Hindu Kush Himalaya initiative supported the World Food Programme

1 Amy McNally et al., "A Land Data Assimilation System for Sub-Saharan Africa Food and Water Security Applications," *Scientific Data* 4, no. 1 (2017): 170012, <https://doi.org/10.1038/sdata.2017.12>.

2 Oleg Bilukha et al., "Famine Review Committee: Combined Review of: (i) The Famine Early Warning System Network (FEWS NET) IPC Compatible Analysis for IDP Camps in El Fasher, North Darfur; and (ii) The IPC Sudan Technical Working Group Analysis of Zamzam Camp (North Darfur), Sudan: Conclusions and Recommendations," *Integrated Food Security Phase Classification*, August 1, 2024, https://www.ipcinfo.org/fileadmin/user_upload/ipcinfo/docs/IPC_Famine_Review_Committee_Report_Sudan_July2024.pdf.

(WFP)'s response to drought and flood emergencies in Nepal and shaped the country's ongoing food security monitoring systems.³

Emergency Response | NASA HARVEST, UN FAO, and the Ministry of Agriculture in Malawi

Satellite data validated against mobile field surveys contributed to assessments of damage to cropland and crop yield forecasts following Cyclone Freddy in Malawi to support relief efforts and agricultural planning.⁴

Operational Support and Program Evaluation | WFP VAM

The World Food Programme's Vulnerability Analysis and Mapping (WFP VAM) unit routinely integrates geospatial data into food security analyses, which inform WFP operations, and the Logistics Cluster's **LogIE platform** aggregates information to support humanitarian coordination, including from satellite data sources.⁵

Accountability and Documentation | Yale Humanitarian Research Lab and Oak Ridge National Laboratory:

The Yale Humanitarian Research Lab and Oak Ridge National Lab used very high resolution (VHR) commercial satellite imagery and custom object detection algorithms to assess conflict-related damage to food storage infrastructure in Ukraine.⁶

See **Appendix C** for further examples.

What are the ethics and risk considerations of introducing the use of satellite data?

General Limitations for EO Data and Models

Earth observation data has important limitations that may shape what data sources and models align with user needs, including:

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- ³ International Centre for Integrated Mountain Development (ICIMOD), "Earth Observation and Geospatial Data Key to Humanitarian Assistance," SERVIR-Hindu Kush Himalaya Initiative, April 13, 2018, <https://servir.icimod.org/stories/earth-observation-and-geospatial-data-key-to-humanitarian-assistance/>; F. M. Qamer et al., "Operationalizing Crop Monitoring System for Informed Decision Making Related to Food Security in Nepal," The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XL-8 (November 2014): 1325–30, <https://doi.org/10.5194/isprsarchives-XL-8-1325-2014>.
 - ⁴ GEOGLAM, Tropical Cyclone Freddy Causes Widespread Damage and Loss to Main Season Crops in Mozambique and Malawi, Crop Monitor Special Report (2023), https://static1.squarespace.com/static/636c12f7f9c2561de642a866/t/65677b1d5e61354334106288/1701280541719/Special_Report_20230425_Southern_Africa.pdf; Food and Agriculture Organization of the United Nations (UN FAO), "From the Soil to the Stars," November 13, 2023, <https://www.fao.org/newsroom/story/From-the-soil-to-the-stars/en>.
 - ⁵ World Food Programme, "WFP VAM," accessed May 20, 2026, <https://dataviz.vam.wfp.org/about-us>.
 - ⁶ Kaveh Khoshnood et al., Post-Invasion Damage Assessment: Ukraine's Crop Storage Infrastructure, ORNL/SPR--2022/2621, 1999083 (2022), ORNL/SPR--2022/2621, 1999083, <https://doi.org/10.2172/1999083>.

Data

Spatial resolution is the area represented by a single pixel in an image and determines the size of the smallest features that can be distinguished. Too coarse spatial resolution may not be able to detect features of interest, such as smallholder fields.

Spectral resolution, or the range of wavelengths a sensor captures, determines what kinds of analysis are possible, and not all sensors carry the bands needed for a given application. For instance, vegetation indices typically require near-infrared (NIR) and red bands.

Revisit frequency, or how often a satellite passes over a given location, sets the cadence at which changing conditions can be observed.

Latency is the delay between image acquisition and availability for analysis and can constrain time-sensitive decisions.

Geographic coverage may be incomplete over the area of interest, and cloud cover can obscure optical imagery, especially during rainy seasons. Finally, accuracy depends on sensor calibration, atmospheric correction, and the validity of underlying algorithms, all of which can vary across products and contexts.⁷

Models

While machine-learning models are not a prerequisite for EO-based analysis, they can help users interpret raw satellite imagery and detect patterns.

The availability of **local training data** shapes whether models can be developed or fine-tuned for a given application. The temporal coverage of training data also matters, since models trained on data from one period or season may not generalize to others, particularly for agricultural applications.

Ground validation through field observations helps confirm that satellite-derived products reflect actual conditions on the ground.

Ground Truth

Beyond these technical constraints lies a more fundamental one: **remote sensing measures observable proxies and correlates, not food insecurity itself**. Satellite data cannot directly capture outcomes such as nutritional status or consumption. What EO captures are visible conditions that have been shown to correlate with food security outcomes under specific circumstances. The strength of those correlations can shift over time and across contexts, so relationships established in one region or period may not hold in another. EO-derived findings therefore provide evidence that must be interpreted alongside qualitative knowledge, ground-based data, and community-level information rather than treated as direct measurements of food security.

Technical expertise must be paired with deep local knowledge. Many analytical judgments that appear technical on the surface — such as distinguishing agricultural burning from conflict-related fire activity or interpreting patterns of market activity — depend on contextual understanding of local practices, seasonal calendars, and the social dynamics of a specific area. EO analysis conducted without this contextual

⁷ NASA Earthdata, “Resolution,” Basic page, Earth Science Data Systems, NASA, December 18, 2025, <https://www.earthdata.nasa.gov/learn/earth-observation-data-basics/remote-sensing-resolution>.

knowledge risks producing misleading conclusions, with serious consequences for the people the analysis is meant to support. Remote sensing also cannot tell decision-makers what assistance people need most or what interventions communities would find most beneficial.

In general, partnerships across local, national, and international actors should be built early, ideally as a foundation laid before emergencies arise. Common entry points for building relationships include partnership offices, embedded liaisons, and capacity-building or training programs. These partnerships should also reflect that local organizations bring more than contextual knowledge and field access; they can also be partners in generating credible evidence themselves and use EO to support their own work rather than serving solely as sources of ground truth for others' assessments.

Tropical Cyclone Freddy

March 2023



Following Tropical Cyclone Freddy, Malawi's Ministry of Agriculture, with support from FAO and NASA HARVEST, assessed flood damage to cropland by combining satellite imagery with field surveys through a mobile app. The field data was critical for training the machine learning models that identified cropland and crop conditions from satellite imagery, particularly for smallholder fields whose boundaries and crop types satellites alone could not easily distinguish. The ground data and interactions with farmers also helped the government of Malawi and aid community understand how the storm affected people on the ground and how to direct assistance to those who needed it most.



GEOGLAM, Tropical Cyclone Freddy Causes Widespread Damage and Loss to Main Season Crops in Mozambique and Malawi, Crop Monitor Special Report (2023), https://static1.squarespace.com/static/636c12f7f9c2561de642a866/t/65677b1d5e61354334106288/1701280541719/Special_Report_20230425_Southern_Africa.pdf; NASA Earth Observatory, Freddy Brings Lean Times to Malawi, Earth Observatory, May 4, 2023, <https://science.nasa.gov/earth/earth-observatory/freddy-brings-lean-times-to-malawi-151289/>; Food and Agriculture Organization of the United Nations (UN FAO), "From the Soil to the Stars," November 13, 2023, <https://www.fao.org/newsroom/story/From-the-soil-to-the-stars/en>.



Limitations of EO Data for Food Security

Earth observation data has further limitations specific to food security applications. These include the following:

Malnutrition

EO data has limited applicability for measuring malnutrition, and foundational measurements such as Weight-for-height Z-scores (WHZ) and mid-upper arm circumference (MUAC) have no remote sensing equivalent. Some research has attempted to use EO data to model malnutrition risk or nutrient content in staple crops, but these approaches estimate factors associated with nutritional status rather than measuring it directly.⁸

Mortality

Alongside acute malnutrition and change in food consumption and livelihoods, mortality is a key reference outcome that can inform the IPC's food security assessments. Satellite imagery analysis of grave sites has contributed to mortality estimates in the IPC's food security assessments in Sudan, as well as in related humanitarian and accountability contexts. Like other indicators discussed above, mortality estimates derived from EO are proxies rather than direct measurements. Satellite imagery can document visible features such as new burial activity, grave dimensions, and changes in cemetery extent, but mortality estimates derived from these observations depend on assumptions about burial practices, individuals per grave, the proportion of deaths captured by visible burials, and other factors which vary across contexts.⁹

Dimensions of Food Security

The IPC framework considers food availability, access, utilization, and stability as distinct dimensions of food security.¹⁰ Of these, remote sensing methods are best suited to food availability, which pertains to whether food is physically present for consumption. In this realm, satellite data can speak directly to contributing measures such as agricultural and pasture conditions, market functionality, and the status of food infrastructure such as grain silos. For other dimensions, satellite data often shifts from a direct measurement role to a supplementary one, providing signals that can triangulate findings

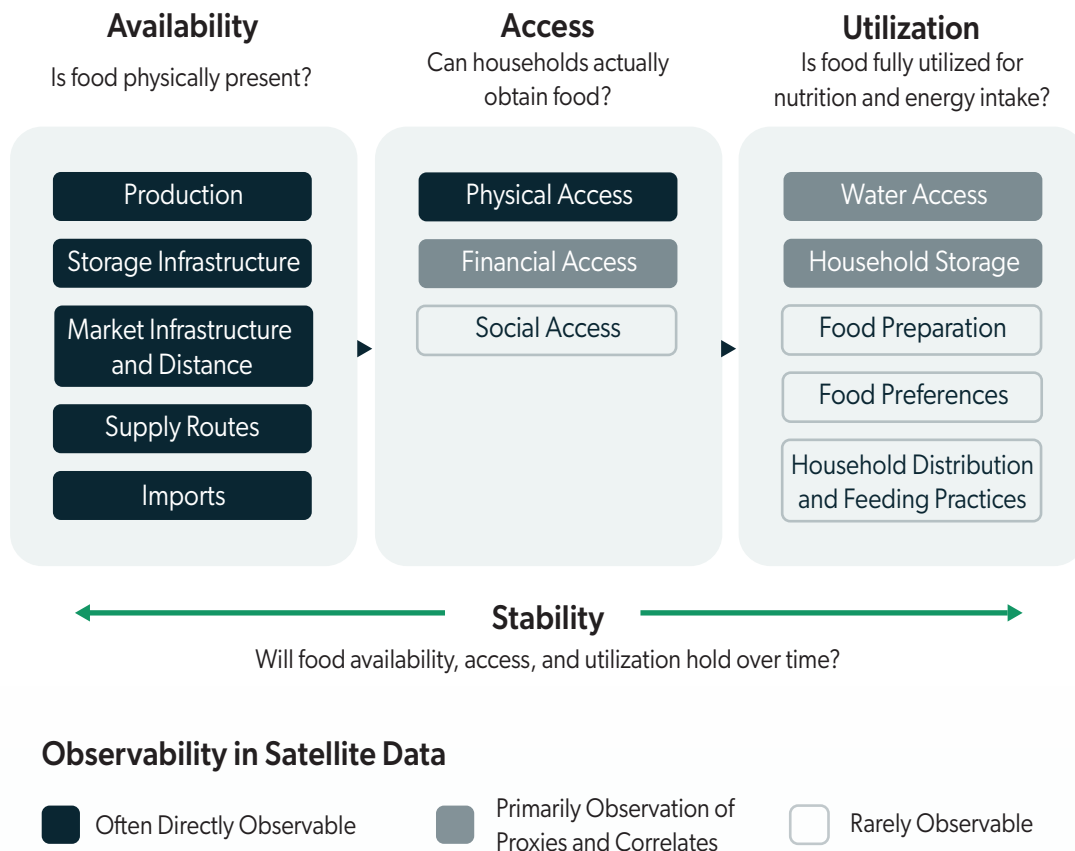
8 Kathryn Grace et al., "Child Malnutrition and Climate in Sub-Saharan Africa: An Analysis of Recent Trends in Kenya," *Applied Geography* 35, no. 1 (2012): 405–13, <https://doi.org/10.1016/j.apgeog.2012.06.017>; European Space Agency, "Measuring Nutrition in Crops from Space," October 10, 2023, https://www.esa.int/Applications/Observing_the_Earth/FutureEO/Measuring_nutrition_in_crops_from_space.

9 Oleg Bilukha et al., "Famine Review Committee: Combined Review of: (i) The Famine Early Warning System Network (FEWS NET) IPC Compatible Analysis for IDP Camps in El Fasher, North Darfur; and (ii) The IPC Sudan Technical Working Group Analysis of Zamzam Camp (North Darfur), Sudan: Conclusions and Recommendations," Integrated Food Security Phase Classification, August 1, 2024, https://www.ipcinfo.org/fileadmin/user_upload/ipcinfo/docs/IPC_Famine_Review_Committee_Report_Sudan_July2024.pdf; Dalton Lunga et al., "Learning to Count Grave Sites for Cemetery Observation Models With Satellite Imagery," *IEEE Geoscience and Remote Sensing Letters* 19 (2022): 1–5, <https://doi.org/10.1109/LGRS.2020.3022328>; Brittany Card and Isaac Baker, "GRID: A Methodology Integrating Witness Testimony and Satellite Imagery Analysis for Documenting Alleged Mass Atrocities," *Genocide Studies and Prevention: An International Journal* 8, no. 3 (2014), <https://doi.org/10.1080/108000085030.2006.10757132>; M. Kalacska and L. S. Bell, "Remote Sensing as a Tool for the Detection of Clandestine Mass Graves," *Canadian Society of Forensic Science Journal* 39, no. 1 (2006): 1–13, <https://doi.org/10.1080/00085030.2006.10757132>.

10 IPC, "Integrated Food Security Phase Classification Technical Manual," 31

drawn from non-EO sources. Satellite data can inform understandings of physical access through measures such as proximity, road functionality, and vehicle presence at markets. However, it contributes only indirectly to populations' financial or social access to food, which may be informed by factors such as gender and ethnicity which cannot be observed remotely. Similarly, satellite data contributes only indirectly to measures of utilization, which is usually determined by food preferences, preparation, and access to complementary needs such as water.

Figure 2: Earth Observation and IPC Food Security Dimensions



Note: Categorization reflects the current state of EO data and methods and is subject to change as the field evolves

Conflict Sensitivity and Protection Risks

In conflict settings, satellite data can reveal the location of settlements, internally displaced populations, or critical infrastructure in ways that may create protection risks for affected communities.¹¹ Imagery that identifies

¹¹ Brittany Card et al., "Satellite Imagery Interpretation Guide: Displaced Population Camps," Harvard Humanitarian Initiative, 2015, <https://hhi.harvard.edu/publications/satellite-imagery-interpretation-guide-displaced-population>; Brittany L. Card et al., "Conflict-Related Displaced Population Camps Commonly Visible in High-Resolution Satellite Imagery Where Do We Go Now: Examining the Causes and Consequences of Mass Displacements and Immigration Policies," Seton Hall Journal of Diplomacy and International Relations 16, no. 2 (2014): 57–76.

an active IDP camp, a functioning market, or a grain store could be misused if it reaches hostile actors. Practitioners should consider who will have access to their analysis and under what conditions it will be shared or published. Two sets of principles should shape these decisions:

Humanitarian Principles

The humanitarian principles of humanity, impartiality, neutrality, and independence must guide decisions about what is analyzed, how results are framed, and with whom they are shared.

Data Protection Principles

While EO data is not itself personally identifiable, the analyses it enables can generate derived products that may be sensitive, especially when combined with other information. Individuals and organizations planning to use EO data should observe core data protection principles of purpose limitation, data minimization, data retention, and data security. Humanitarian actors should consider conducting a preliminary assessment before collecting any data to identify risks and mitigation measures before analysis begins.

Additional guidance is available from the [OCHA Data Responsibility Framework](#), the [Berkeley Protocol on Digital Open Source Investigations](#), the [Harvard Humanitarian Initiative's Signal Code](#), and [ICRC's Handbook on Data Protection in Humanitarian Action](#).

To Consider...

Carefully assess whether to publicly release potentially actionable information, such as the locations of vulnerable populations or critical food infrastructure, in conflict-affected contexts.

What data could support these decisions? What are 'must have' requirements?

Definitions of core and optional data depend on the ultimate goal of analysis. **Table 1** presents examples of common food security applications, grouped into three categories, along with parameters and dashboards that may be relevant to each. These examples are not exhaustive. They are also illustrative rather than prescriptive: not every parameter or dashboard listed in a given row applies to each of the given applications, and the precise data and tools appropriate for any particular analysis depend on what is being analyzed, how, and where. This table is intended to orient practitioners to the landscape of relevant data and tools, not to serve as definitive technical guidance.

For step-by-step instructions on accessing and working with specific datasets, see the companion **Agriculture & Food Security Data Studio Package**, as well as related NASA Lifelines Data Studio Packages referenced throughout the table.



Table 1: Food security applications, parameters and dashboards

Application	Example Parameters	Example Existing Dashboards
Environment and Agriculture <i>Earth observation data can help analyze and forecast environmental variables that inform food security conditions. This information can support food security assessments, future food security forecasting, and ongoing monitoring and evaluation of food security programs.</i>		
Vegetation: Vegetation and rangeland health, agricultural analysis	Vegetation Indices e.g., normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), leaf area index (LAI)	NASA GLAM, GEOGLAM Crop Monitor, FEWS NET Data Explorer
Cropland: area assessment and type mapping	Multispectral imagery (NIR, SWIR bands), SAR, derived land cover and crop type products	ESA WorldCereal, GEOGLAM Crop Monitor
Water availability: drought monitoring and agricultural forecasting	Soil moisture, evapotranspiration, evaporative stress index (ESI), precipitation	CHIRPS Early Warning Explorer, FEWS NET Agroclimatology, FAO WaPOR
Food Systems: Damage Assessments and Access to Food <i>Earth observation data can provide information about food systems, including damage to food sources and infrastructure, as well as social indicators for access to food. This data can inform both food security assessments and accountability efforts for attacks on critical infrastructure.</i>		
Cropland damage assessment: Flooding	SAR, surface water, NRT flood products	NASA Flood Viewer, Copernicus CEMS GloFAS, Google Flood Hub, WFP ADAM Floods See NASA Lifelines Flood Early Warning Data Studio Package
Cropland damage assessment: Fire	Multispectral imagery (NIR, SWIR bands), NRT active fire data	NASA FIRMS, Global Wildfire Information System See NASA Lifelines Wildfire Early Warning and Rapid Response Data Studio Package

Damage to food infrastructure (including conflict-related)	SAR, VHR optical imagery	Copernicus EMS Rapid Mapping, UNITAR-UNOSAT Damage Assessments, NASA ARIA Damage Proxy Maps See NASA Lifelines Building Damage Assessment Data Studio Package
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Food access (e.g., pattern of life assessment at markets and fields)	VHR optical imagery	N/A (typically custom analysis)
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Operational Support

Satellite data can support emergency assistance, including through the location of vulnerable populations and route planning.

Aid targeting (e.g., location of displaced populations)	VHR optical imagery	N/A (typically custom analysis)
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Route planning (e.g., damage to roads/airports, unexploded ordnance, security conditions)	SAR, VHR optical imagery	N/A (typically custom analysis)
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See the [Agriculture & Food Security Data Studio Package](#) from NASA Lifelines for further guidance

While other remote sensing platforms such as unmanned aerial vehicles (UAVs), aircraft, and ground-based instruments also offer valuable capabilities for food security applications, this case study focuses specifically on space-based Earth observations.

Analysis of EO data can also be supplemented with non-satellite data sources. These might include the following:

- **Environmental and Geophysical:** [Google Open Buildings](#) and [OpenStreetMap](#) building footprints, data on physical features such as water bodies and roads, and administrative boundaries.
- **Population and need:** [ACLED](#) conflict data, [IOM Displacement Tracking Matrix](#) migration data, UN OCHA Humanitarian Needs and Response Plan (HNRP) and People in Need (PiN) per [Joint and Intersectoral Analysis Framework \(JIAF\)](#), and demographic and health surveys.
- **Food security-related:** [IPC](#) and [FEWS NET](#) assessments; market assessments (including from [WFP](#)), mobile field surveys, and national or international agriculture and livestock censuses where applicable. The WFP-VAM [Data Bridges API](#) provides programmatic access to household survey data, market prices, food security indicators, and other WFP monitoring data.

FAO's [Hand-in-Hand Geospatial Platform](#) aggregates geospatial layers and other datasets across food security, agriculture, climate, and natural resources.

To Consider...

Commercial vs. Publicly Available Data

Sub-meter VHR data from commercial providers is often necessary for the most granular applications related to monitoring changes to people, vehicles, and structures (e.g., in assessing food infrastructure and population movements), as well as for smallholder agricultural environments where widely available data lacks sufficient spatial resolution. However, cost and company policy can limit timely access, particularly for imagery of active conflict zones. Practitioners should contact commercial providers directly to develop lasting partnerships before a crisis occurs and ask about eligibility for crisis response or humanitarian access programs, which can provide imagery at reduced or no cost. UN agencies and organizations with relationships to the U.S. government or to national disaster management authorities may also be able to access imagery through programs such as the [International Charter on Space and Major Disasters](#) or NASA's [Commercial Satellite Data Acquisition \(CSDA\)](#) program and should review eligibility criteria. In general, practitioners without specialized access should identify free and open alternatives including [ESA Copernicus/Sentinel data](#), [NASA Landsat](#), and [NASA HARVEST](#) products as the foundation of their analytical workflows.

What's our Approach?



This section helps decisionmakers design an approach to incorporating EO data into their organization's specific institutional context and constraints. Before working through these questions, organizations may benefit from conducting a structured assessment of their current programs, capabilities, and infrastructure. This kind of assessment can clarify what spatial data is already being collected or used, as well as any organizational gaps. For instance, Mercy Corps' [Spatial Data Readiness Assessment](#) provides a publicly available methodology that other organizations can adapt to their own contexts.

Do any existing solutions meet our requirements? If not, what gaps exist?

Several established platforms and data products already deliver EO-based food security analyses and may meet some or all of an organization's requirements without the need to build custom workflows. Examples of widely used platforms are below:

- **WFP HungerMap LIVE:** A near-real-time food security monitoring platform that integrates EO data with market price, conflict, and livelihood indicators.
- **FEWS NET Data Explorer:** Combines satellite rainfall estimates, vegetation indices, and seasonal forecasts with food security analysis for chronically food-insecure countries.

- **NASA HARVEST GLAM:** Near real-time global agricultural monitoring using MODIS and other satellite data, with historical baselines extending back decades. Particularly strong for crop condition monitoring and early warning.
- **GEOGLAM Crop Monitor:** Provides monthly assessments of crop conditions globally, integrating satellite data with national agricultural statistics and field observations.
- **ESA WorldCereal:** Provides seasonal crop type maps and crop calendars for major staple cereals, supporting cropland extent assessment and yield-relevant monitoring.
- **WFP ADAM** and **FAO EVE:** ADAM issues near-real-time alerts and impact dashboards following disasters (though full dashboard access is limited to registered humanitarians), while EVE's biweekly map dashboard offers openly accessible food insecurity monitoring in fragile environments.
- **UNOSAT:** Provides rapid satellite-derived damage and crisis mapping and has been used to assess damaged cropland and food infrastructure.

See list of additional dashboards and derived products in **Appendix A**.

Existing tools are likely to meet practitioner needs for environmental and climate monitoring. However, general tools may lack granularity required for highly local analysis or very high-resolution applications, and practitioners may want to adapt existing tools to examine specific parameters or use cases. Ground truthing and local validation are also critical inputs that are often absent from general tools, and practitioners should identify opportunities to incorporate community- or partner-held local knowledge as a validation source wherever possible.

What types of skills and expertise are needed? Based on our internal capacity and bandwidth, can our teams take on this work? What kinds of partnerships do we need?

Effective use of EO data for food security work depends on combining several distinct and essential kinds of expertise:

1. **Technical expertise:** familiarity with geographic information systems (GIS) and remote sensing workflows, including for food security applications
2. **Domain expertise:** familiarity with local context and food security dynamics
3. **Implementation expertise:** understanding of and access to decision-making processes around food security

Organizations should consider whether they can host all three in-house or whether some areas are best accessed through partnerships. **Appendix B** provides decision support tools to facilitate communication across teams with different areas of expertise. These include a **Decision Scoping Tool** template to assist technical partners in designing their analysis to fit decision needs, as well as a **Technical Scoping Tool** template so that operational partners can request, interpret, and use outputs responsibly.

The level of expertise required also scales with the complexity and customization of the analysis being undertaken. Different kinds of analysis place very different demands, and organizations should match the level of analysis to the expertise available rather than attempting more sophisticated work than their team can support.

Basic Implementation (existing dashboards and monitoring platforms)

Basic digital literacy and food security knowledge are likely sufficient for accessing and interpreting existing dashboards. No specialized remote sensing expertise is required.

- E.g., FEWS NET, GLAM, WFP HungerMap

Intermediate Analysis (extracting and analyzing satellite indicators)

GIS or data analysis skills are needed, along with familiarity with remote sensing concepts and local context. Manual VHR analysis requires significant local knowledge for interpretation. Practitioners at this level can customize analysis for specific areas of interest but rely on established methods and datasets.

- E.g., Google Earth Engine scripts, standardized GIS workflows, manual VHR analysis

Advanced Analysis (building integrated monitoring systems)

Remote sensing specialists, data scientists, and domain experts are required. This level of analysis typically demands dedicated personnel, significant computing resources, and substantial time investment. Accordingly, this kind of analysis should be reserved for personnel with the requisite expertise, often in a dedicated research or technical role.

- E.g., Custom machine learning models, yield estimation, crop type mapping

See the [Food Security Data Studio Package](#) for implementation guidelines. Across these levels of analysis, implementation expertise is required for application and implementation of food security analysis products. Given the weight these analyses can carry in decisions affecting vulnerable populations, they should be conducted only by personnel with the requisite expertise and resources.

To Consider...

Artificial intelligence (AI)

AI can transform how humanitarian actors utilize Earth observation data. Increasingly sophisticated AI models and agents can expand analytical capacity, particularly through rapid analysis of large EO datasets. At the same time, not every GeoAI tool is appropriate for every operational environment, and many tools fall short of technical and ethical safeguards required for responsible use in high-stakes settings across dimensions such as trust, safety, efficacy, equity, and accountability. For further guidance, see NASA Lifelines' [GeoAI for Humanitarian Action](#) report.

Partnerships

A key challenge identified by practitioners is the silo between nutrition and health practitioners, other humanitarian actors, and remote sensing experts. Building these connections is as important as any technical capacity investment, and leaders have a responsibility to create the incentives, structures, and culture of collaboration. Organizations that do not have the capacity to host all areas of expertise in-house may rely on a

liaison model with points of contact across organizations with different expertise. Regardless of where different forms of expertise lie institutionally, experts must align on and clearly communicate needs, capacity, and capabilities.

There are also groups that can help support the use of satellite data and tools for agricultural and food security analysis if in-house technical capacity is limited. This includes organizations like NASA Lifelines, **NASA Applied Remote Sensing Training Program**, the **GEO Global Agricultural Monitoring initiative**, and the **Earth Observation Training, Education, and Capacity Development Network**.

Figure 3: Examples of Organizations with Different Expertise



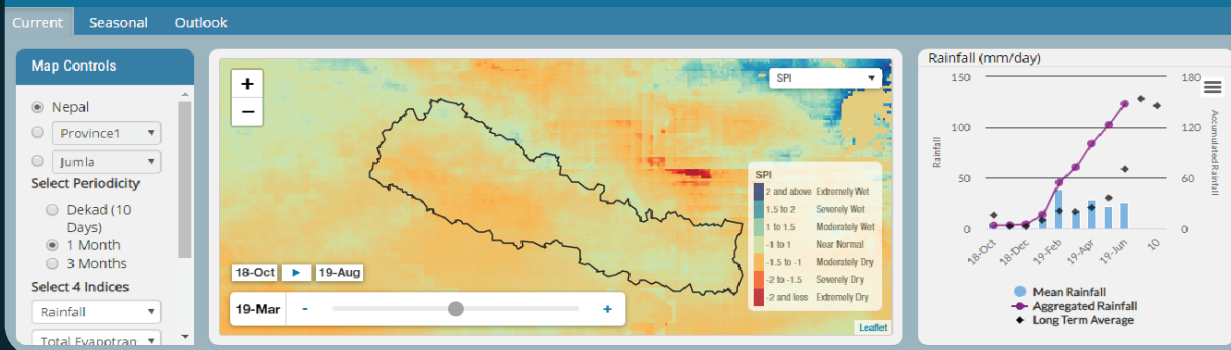
Drought in Western Nepal 2016



Through SERVIR-Hindu Kush Himalaya, NASA and USAID collaborated with the World Food Programme and the International Centre for Integrated Mountain Development (ICIMOD), an intergovernmental organization based in Kathmandu, to respond to the 2016 Western Nepal drought and subsequent flood emergencies. This partnership brought together technical expertise in EO analysis, domain expertise in regional and food security dynamics, and implementation expertise in humanitarian operations, allowing scientific analyses to be tailored to local conditions and directly integrated into response decisions. SERVIR currently operates without U.S. government involvement through the **SERVIR Global Collaborative**.

National agricultural drought watch - Nepal

ICIMOD





What data, tools, standards, and techniques are already adopted and trusted by humanitarians? What is my team familiar with? How can we know we’ve covered everything?

Integrating EO analysis into existing and trusted systems may increase the likelihood that findings will be operationalized and sustained. The categories below identify validated platforms and common touchpoints worth considering when designing an approach to EO-enabled food security work:

Data

Many local partners and food security actors already integrate spatial data in some form. For instance, agricultural ministries may maintain crop production statistics by administrative unit. EO data is most likely to be trusted and used when it is framed as extending or strengthening these existing workflows rather than replacing them.

Platforms

Partners may already be using certain platforms that can incorporate EO data. Teams familiar with **QGIS**, **ArcGIS**, or **Google Earth Engine** can often incorporate EO data (or different sources of EO data) with relatively modest additional training; those without any GIS capacity may be better served by ready-made dashboards than by raw data access.

Standards

The IPC is the globally accepted standard for food security severity classifications. The **IPC Technical Manual** also provides a framework for understanding food security, including scales (chronic food insecurity, acute food insecurity, and malnutrition) and dimensions (availability, access, utilization, and stability).

Products

FEWS NET early warning products are already embedded in the workflows of major donors, UN agencies, and many NGOs. Analysts who can connect their outputs to FEWS NET findings or terminology are more likely to be understood and used.

New datasets, methods, and tools emerge regularly, and organizations should plan for ongoing learning and engagement with the broader EO and food security communities. Sustained relationships with partners and mechanisms for staff to follow developments in the field are all part of maintaining capacity over time.



Which data is open and accessible for us and our partners? Who needs access to the data? Any sensitivities on who gets access or when?

The majority of EO data relevant for environmental monitoring of food security is freely available. These include the following:

- **NASA:** Landsat (vegetation indices, surface reflectance, land surface temperature); MODIS and VIIRS (vegetation, fire, and flood products); GPM (precipitation); SMAP (soil moisture); ECOSTRESS (evapo-transpiration and water stress); OPERA DSWx (surface water), NISAR (land surface change).
- **ESA Copernicus:** Sentinel-1 (SAR, all-weather flood and crop mapping) and Sentinel-2 (multispectral vegetation indices and crop monitoring) are free and widely used for humanitarian agricultural analysis.
- **CHIRPS** and **ECMWF:** Widely used datasets for monitoring and forecasting precipitation and weather conditions that drive agricultural productivity and food insecurity. CHIRPS provides high-resolution historical and near-real-time precipitation estimates, while ECMWF offers broader global weather forecasts and reanalysis data.

Many users may not need a wide variety of EO data sources, and various organizations have aggregated food security-relevant datasets, including **NASA Earthdata** and the **ATAI Data Portal**.

Open-source satellite data can typically be shared freely. Very high-resolution or derived products should be governed by data access protocols informed by the **ICRC Handbook on Data Protection in Humanitarian Action**. Access restrictions are important in the following cases:

- **Restricted Data:** Data from commercial providers or accessed under specific contracts may be subject to end-user licensing agreements or contractual obligations regarding sharing and release.
- **Sensitive Data:** Products that reveal sensitive data, such as the location of vulnerable populations or critical infrastructure can be misused in conflict settings. Consider whether to share full spatial products or only summary findings, as well as whether findings need to be shared publicly or only to select partners.
- **Non-Humanitarian Actors:** When products are shared with governments, military actors, or other parties outside the humanitarian system, the humanitarian principles of neutrality and independence require careful consideration of whether and how that sharing occurs.



What will this approach cost (in team time, data purchases, travel, etc.)? Is it worth the investment? Are there free/more affordable alternatives?

While EO-based food security analysis does carry real costs, it remains achievable even for organizations with limited resources. These costs can vary but generally fall into three categories:

- **Personnel time:** Personnel time is the dominant cost for most analytical approaches. Training staff, building and validating models, interpreting outputs in context, and communicating results to decision-makers requires significant expert time. Institutional partnerships that enable systematic EO use are also often built gradually. These investments are difficult to avoid without harming analytic validity.
- **Data:** Data costs are minimal for open-source datasets and workflows. However, VHR commercial imagery can be expensive. Some commercial providers offer humanitarian discounts or emergency data access programs, so practitioners should inquire early.
- **Compute and storage:** Computing and storage costs can be reduced with cloud platforms, such as Google Earth Engine, a cloud-based platform hosting petabytes of EO data, along with limited free-compute for noncommercial accounts. Additionally, cloud storage platforms such as AWS and Azure may offer research and nonprofit discounts.

For many food security applications focused on agriculture, existing operational products such as GLAM and FEWS NET dashboards provide substantial value without any additional analytical investment. Custom analysis should be pursued only when these platforms do not answer the specific decision-relevant question.

How much time do you need to gather data? For analysis?

Decision-making timelines are a critical input to tool selection. Analyses that cannot be produced within a decision window are not actionable, regardless of quality. Data collection and analysis timelines vary significantly by use case:

- Accessing and visualizing existing operational products can be done within hours for a user already familiar with the platforms.
- Producing a customized weather or agricultural analysis for a specific area of interest, using existing methods and freely available data may require days to weeks depending on analyst experience and the complexity of the area.
- Developing a new dataset or workflow, including model training and accuracy validation, may require weeks to months and depends on availability of ground truth data, especially in inaccessible environments.

Time requirements could stretch longer, especially in environments with limited resources.

What are your needs for analysis like cloud computing, internet bandwidth, team time, other expertise, and in-country partners?

Most food security EO analysis can be conducted with freely available, web-based tools and does not require specialized computing infrastructure. A reliable internet connection is required for accessing most operational platforms and cloud computing environments. In settings with severely constrained connectivity, practitioners should identify which data can be downloaded and processed offline in advance.

- GIS software (including QGIS, which is free) or access to Google Earth Engine is sufficient for most intermediate-level analysis.
- For processing large volumes of data or more advanced workflows, code-based approaches offer greater flexibility. Large language models can help practitioners set up these workflows but may require additional technical expertise to establish and review.

The Mercy Corps [Reduced Access Analytical Methods Toolkit](#) explicitly emphasizes methods accessible in low-bandwidth environments, including for remote sensing.

Sharing and Communicating Results



This section helps practitioners translate EO analysis accurately and responsibly to inform humanitarian decision-making. The sections below cover considerations for how to characterize the reliability of findings, how to communicate risks and limitations, what elements of an approach are worth sharing externally, and how to evaluate impact. Given the stakes of humanitarian work, clear and honest communication is essential in outlining assumptions and limitations.

How accurate are the data, analysis, and findings?

All EO products carry uncertainty. This includes direct observations and modeled products. In humanitarian settings, ground truth data to validate EO findings is also often limited. While accuracy requirements depend on use case, audiences often assume that satellite data arrives in real time with perfect resolution and no measurement error. Analysts have a responsibility to correct this assumption proactively and adopt a methodology for assessing accuracy, such as ground-truthing or peer-reviewing models.

For food security, previously described limitations of EO-based approaches in areas such as malnutrition, yield estimates in smallholder settings, and measures of food access, utilization, and stability should be clearly communicated.

How should we communicate about risks and uncertainty?

Uncertainty should be communicated clearly and in plain language for humanitarian audiences. Analysts should explicitly flag where their analysis depends on assumptions that may not hold; for example, that a decline in vegetation reflects reduced crop production rather than a shift in cropping calendar, or that market inactivity reflects access constraints rather than regular weekly patterns.

Uncertainty communication should also be tailored to the context of analysis. Analysts often face a tradeoff between timeliness and confidence: faster turnarounds, commonly required in urgent humanitarian situations, typically come with wider uncertainty that should be explicitly communicated to decision makers. Uncertainty communication may also depend on the intended use of the analysis. An estimate used to trigger increased monitoring of an area requires a lower precision threshold than one used to justify large-scale resource deployment or a formal famine classification.

Effective uncertainty communication is fundamentally about maintaining trust and credibility. The communicator should be able to accurately convey limitations while sustaining confidence in the estimates, and they should be sensitive to the fact that food security classifications can carry significant political weight and real consequences for the communities they describe.

Are there elements of our approach that should be shared?

Open science and responsible data sharing are both valuable and achievable in most food security EO applications. While observing responsible data sharing principles, practitioners should consider the following:

- Document and share methodologies, code, and analytical workflows where possible, contributing to the growing body of replicable humanitarian EO practice. Platforms such as [GitHub](#) support this sharing.
[NASA HARVEST](#) and [WFP-VAM](#) both publicly share code, pretrained models, and datasets through GitHub repositories, enabling practitioners to adapt existing tools for cropland mapping and food security analysis.
- Share non-sensitive derived products such as crop condition assessments and damage estimates, ensuring that other humanitarian actors can access and build on them. [Humanitarian Data Exchange](#) is the standard platform for all shareable humanitarian data products.
- Identify and document where analytical approaches did not work, and why. Environmental variables interact with food production systems in complex and context-specific ways. Methods that perform well in one agroecological zone or conflict context may fail in another.
- Consider whether outputs could be integrated into existing early warning or monitoring systems for policymakers and humanitarian organizations rather than existing as standalone deliverables.

Data protection and humanitarian principles should be central to decisions around what information should be shared and with whom. Particularly in conflict and other crisis environments, the category of sensitive information becomes context-dependent in ways that conventional data protection does not anticipate.

What was the impact of our decision-making using this data/analysis?

Impact in humanitarian EO work can be assessed along many dimensions, and practitioners should adapt their approach to evaluation based on what the analysis was meant to support. The examples below illustrate dimensions worth considering but are not exhaustive, and the relevant criteria will vary by project:

Impact in humanitarian EO work can be assessed along many dimensions, and practitioners should adapt their approach to evaluation based on what the analysis was meant to support. The examples below illustrate dimensions worth considering but are not exhaustive, and the relevant criteria will vary by project:

- **Informational impact:** Did the analysis provide decision-makers with information on the nature or spatial distribution of food security they did not previously have? Did this information corroborate or challenge existing understandings?
- **Decision impact:** Did the analysis influence actual decisions about allocation of resources such as emergency food assistance, advocacy messaging, or famine determination? Did it enable earlier action, such as anticipatory assistance before populations reached more severe food insecurity conditions?
- **Distributional impact:** Did EO-informed decisions and information reach the populations most affected by food insecurity, including those most likely to be excluded from formal information channels and assistance programs? Were satellite-derived insights accessible and beneficial for the populations they were intended to serve?
- **Operational impact:** Did better situational awareness translate into more efficient or targeted food assistance? Did it help provide assistance to populations that hadn't previously been identified?
- **Accountability impact:** Did EO-based documentation of conflict-related agricultural destruction contribute to famine accountability processes, influence donor attention, or support legal mechanisms?

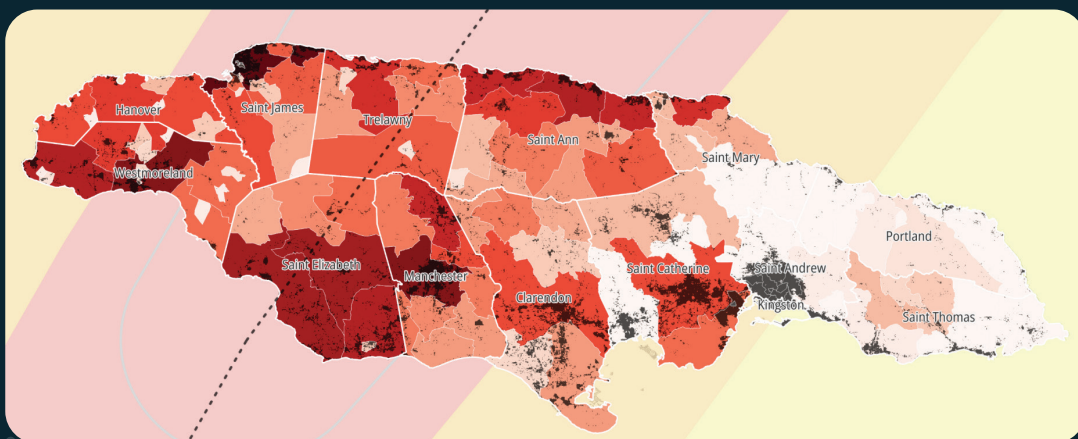
For most humanitarian organizations, the most useful outputs are not necessarily the most technically complex but rather those that are easily interpretable and translate easily into operational tasks.

Hurricane Melissa

October 2025



After Hurricane Melissa made landfall in the Caribbean, the World Food Programme used Earth observation data to support anticipatory action and emergency response. Satellite imagery was used to assess exposure to hazardous wind, flooding, and storm surge conditions, and Sentinel-1 SAR data enabled building damage counts. These analyses fed directly into WFP's emergency response, including approximately US \$1M in cash transfers ready for activation in Jamaica, 600+ pallets of prepositioned relief supplies in Barbados, and 280 metric tons of food moved to eastern Cuba.





In retrospect, would we use satellite data again? What do we want to do differently next time?

Reviewing prior work can help teams refine their approach and build institutional knowledge about when and how EO contributes to food security programs. The questions below are intended to prompt evaluation of how EO data contributed to improved food security outcomes:

Did we capture the right processes, at the right spatial and temporal scales?

Agricultural and food system dynamics are highly context specific. Were the EO indicators we chose truly sensitive to the food security dynamics we were trying to understand, or did we measure what was available rather than what was relevant?

Did we adequately represent what EO cannot see?

Satellite data measures predictors and correlates of food security conditions but not food security outcomes such as malnutrition or starvation themselves. Certain aspects of food security, such as food availability, are more likely to be measured by satellite data than others, such as food access, utilization, and stability. Did we communicate clearly which dimensions of food security our analysis addressed and which it did not, and did decision-makers understand those boundaries and limitations when acting on our findings?

Were we sufficiently connected to in-country partners?

Analyses conducted without meaningful engagement with local agricultural actors, food security clusters, or affected communities are more likely to miss important contextual nuances and less likely to be trusted and used by those responsible for response.

Did we contribute to existing analytical systems or create parallel ones?

Analyses may duplicate or even undermine national agricultural monitoring systems, as well as the existing robust collection of food security products from organizations such as FEWS NET and others. It may be more effective to strengthen existing systems instead of replacing them.

Finally, integration of new data sources such as EO will likely be an iterative process. Teams should plan ongoing feedback loops with end-users, as well as invest in time for teams to iterate on approaches.

Conclusion

Food insecurity and famine remain among the world's most severe humanitarian challenges. From early warning to emergency response and documentation, Earth observation data can transform how humanitarian actors support populations in need, and EO is increasingly accessible even to organizations with limited technical background or resources. Still, the value of satellite data depends on careful matching of tools to decisions, integration with non-EO evidence, the institutional and analytical capacity to interpret findings in context, and adherence to ethical principles that protect the rights and safety of affected populations. The questions raised throughout this case study are intended to help practitioners think through these considerations before committing to a particular approach.

Food security crises rarely occur in isolation; they often emerge in complex environments alongside other challenges such as conflict, displacement, disease outbreaks, and natural hazards. NASA Lifelines provides a broader set of Decision-Making Guides and Data Studio Packages addressing related humanitarian applications of satellite data, including **disease risk modeling**, **damage assessment**, **flooding**, **wildfire**, and **landslides**, among others. Practitioners working at the intersection of food security and other humanitarian needs may find these resources useful for designing integrated analytical approaches.

Earth observations should be understood as one contributor to a broader evidence base that includes local and ground-based knowledge. When scoped and communicated appropriately, satellite data can strengthen the analytical foundation of humanitarian decision-making. Ultimately, the success of EO in humanitarian work should be measured not by technical benchmarks alone, but by whether it tangibly benefits the populations it is intended to serve.

Glossary

ACLED: Armed Conflict Location and Event Data Project

AI: Artificial Intelligence

API: Application Programming Interface

ARIA: Advanced Rapid Imaging and Analysis

ARSET: Applied Remote Sensing Training Program (NASA)

ASAP: Anomaly Hot Spots of Agricultural Production (European Commission Joint Research Centre)

CEMS: Copernicus Emergency Management Service

CHIRPS: Climate Hazards Group InfraRed Precipitation with Station data

CSDA: Commercial Satellite Data Acquisition (NASA)

DTM: Displacement Tracking Matrix (IOM)

ECOSTRESS: ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (NASA)

EMS: Emergency Management Service (Copernicus)

EO: Earth Observation

ESA: European Space Agency

ESI: Evaporative Stress Index

EU: European Union

EVI: Enhanced Vegetation Index

FAO: Food and Agriculture Organization of the United Nations

FEWS NET: Famine Early Warning Systems Network

FIRMS: Fire Information for Resource Management System (NASA)

FLDAS: FEWS NET Land Data Assimilation System

GADAS: Global Agricultural and Disaster Assessment System (USDA)

GEOGLAM: Group on Earth Observations Global Agricultural Monitoring Initiative

GIEWS: Global Information and Early Warning System on Food and Agriculture (FAO)

GIS: Geographic Information System

GLAM: Global Agriculture Monitoring (NASA HARVEST)

GPM: Global Precipitation Measurement (NASA)

HNRP: Humanitarian Needs and Response Plan

ICRC: International Committee of the Red Cross

IDP: Internally Displaced Person

IOM: International Organization for Migration

IPC: Integrated Food Security Phase Classification

JIAF: Joint Intersectoral Analysis Framework

LAI: Leaf Area Index

MODIS: Moderate Resolution Imaging Spectroradiometer

MUAC: Mid-Upper Arm Circumference

NASA: National Aeronautics and Space Administration

NDVI: Normalized Difference Vegetation Index

NIR: Near-Infrared

NRT: Near-Real-Time

OCHA: United Nations Office for the Coordination of Humanitarian Affairs

ORNL: Oak Ridge National Laboratory

PIN: People in Need

SAR: Synthetic Aperture Radar

SMAP: Soil Moisture Active Passive (NASA)

SWIR: Short-Wave Infrared

UN-SPIDER: United Nations Platform for Space-based Information for Disaster Management and Emergency Response

UNITAR: United Nations Institute for Training and Research

UNOSAT: United Nations Satellite Centre (operated by UNITAR)

USDA: United States Department of Agriculture

USGS: United States Geological Survey

VAM: Vulnerability Analysis and Mapping (WFP)

VHR: Very High-Resolution

VIIRS: Visible Infrared Imaging Radiometer Suite

WFP: World Food Programme

WHZ: Weight-for-Height Z-score

Appendix A: Key Resources and References

See [Agriculture & Food Security Data Studio Package](#) for further guidance.

Data

[ATAI Data Portal](#)
[CHIRPS](#)
[ECMWF](#)
[FAO Hand-in-Hand Geospatial Platform](#)
[FAO-UNESCO Digital Soil Maps of the World](#)
[FEWS NET Data Explorer](#)
[Fields of the World](#)
[NASA Food Security Data and Tools](#)
[NASA GLAM](#)

Dashboards and Derived Products

[CHIRPS Early Warning Explorer](#)
[ESA WorldCereal](#)
[EU ASAP](#)
[FAO EVE](#)
[FAO GIEWS](#)
[FAO WaPOR](#)
[FEWS NET](#)
[GEOGLAM Crop Monitor](#)
[UNOSAT](#)
[USDA GADAS](#)
[WFP ADAM](#)
[WFP HungerMap LIVE](#)

Guidance, Training, and Methodological Resources

AidData: [Toolkit for Agricultural Geospatial Impact Evaluations](#)
Google Earth Engine: [Documentation](#)
Harvard Humanitarian Initiative: [Satellite Imagery Interpretation Guide for Displaced Populations](#)
IPC Global Partners: [Integrated Food Security Phase Classification Technical Manual Version 3.1: Evidence and Standards for Better Food Security and Nutrition Decisions](#)
Mercy Corps: [Reduced Access Analytical Methods Toolkit](#)
Mercy Corps: [Are We Geo-Ready? A Landscape Analysis on Spatial Data Readiness at Mercy Corps](#)
NASA ARSET: [NASA/USG Platforms & Instruments with Agricultural Applications](#)
NASA ARSET: [Satellite Remote Sensing for Agricultural Applications](#)
NASA HARVEST: [GitHub](#)
NASA Lifelines: [GeoAI for Humanitarian Action](#)
SkyFi: [High-Resolution Satellite Imagery Guide 2026](#)
UN-SPIDER: [Recommended Practice — Burn Severity Mapping in Google Earth Engine](#)
WFP VAM: [GitHub](#)

Appendix B: Decision Support Tools

These paired tools aim to facilitate the alignment of needs and capabilities between humanitarian and technical teams. Communication is critical to humanitarian workflows that integrate satellite data, especially as expertise may be widely distributed across an organization or a partnership. These tools are intended to support the early stages of a project, when operational and technical partners are determining what analysis to conduct and how it will be used. They surface the questions likely to shape that engagement, but they are not exhaustive. Other considerations will emerge as the partners work together, and the tools are meant to start the conversation rather than end it. Each tool is completed by one side of the partnership and shared with the other.

Continue on next page.

Decision Scoping Tool

To be completed by operational partners (e.g., humanitarian organizations, government agencies, or other end users of EO-informed analysis). The goal is to communicate decision context, information needs, and constraints to technical partners before analytical work begins, so that EO analysis can be designed to fit the decisions it is meant to support. This tool is intended to serve as a starting point for scoping conversations rather than an exhaustive checklist.

Decision Context

- What decision or set of decisions does this analysis need to inform?
- What information do you already have, and where are the gaps? What information would meaningfully change the decision?
- Could any geographic or environmental factors inform the decision? For instance, do you need to know something's location, spatial extent, or concentration? Do you need to know how observable conditions are changing over time? Is environmental information such as weather, climate, or vegetation relevant?
- Are there local or contextual factors that could influence interpretation of the imagery (e.g., agricultural burning vs. conflict-related fire activity)? Are there non-observable factors that could shape our understanding of the situation and conclusions?

Data and Methodological Considerations

- When does the decision need to be made, and how quickly do you need the analysis? Note the timeline, including any fixed deadlines, recurring cycles, or trigger conditions.
- What granularity or spatial resolution is needed? Are there particular objects you want to see?
- How often do you need new information? Could the end product be static?
- What is your area of interest, and how does it relate to existing geographic divisions? Identify the relevant jurisdictional bounds or affected areas.
- Are there factors that could limit applicability of certain satellite data (e.g., cloud cover in the rainy season)?
- What level of precision or confidence is needed? Indicate whether the decision can be supported by directional indicators (change compared to a baseline) or whether it requires quantitative thresholds.
- What protection or sensitivity considerations apply? Identify any data responsibility, access restrictions, or risks that may affect how analysis can be conducted, shared, or used.

Communication

- Who is the primary point of contact for questions during the analysis?
- Who is the audience for this product, and who will make this decision?
- Who is communicating these findings, and how can findings be made accessible? For instance, what is the comfort level of the audience with this language and these methods? Are there local naming conventions or reference points that would be useful to include?
- Should the analysis integrate with any existing systems, standards, or workflows?
- Would particular end products (e.g., static maps, integrated dashboards, action-based alerts, app-based maps, raster images, data tables, situation reports) be most useful?
- When should results be communicated? Identify any required cycles for updates.
- What feedback mechanism will be used after the analysis is delivered?

Technical Scoping Tool

To be completed by technical partners (remote sensing analysts, data scientists, or other developers of satellite data products). The goal is to communicate how EO can support decision making so that operational partners can request, interpret, and use outputs responsibly. This tool is intended to serve as a starting point for scoping conversations rather than an exhaustive checklist.

Analytical scope and approach

- What EO parameters could be useful for the stated end goal? What specific questions would this approach address, given the decision needs communicated by the operational partner?
- What questions cannot be addressed with EO, or only indirectly? Identify dimensions of the decision question that satellite data cannot directly measure (e.g., nutritional status, financial access, household consumption), as well as those it can address only as a proxy or correlate.
- What ancillary data could strengthen the analysis? Note any non-satellite or ground sources (official data, local reports, etc.) for availability and credibility assessments.

Data and Methodological Considerations

- What are the constraints of the chosen satellite parameters? Note relevant limits on spatial resolution, spectral resolution, revisit frequency, latency, geographic coverage, and cloud cover for the area and season of interest.
- What is EO data unable to capture that could be relevant to the decision?
- Have the proposed methods been validated for this population or context? Indicate where methods may not be fit for this use case, as well as constraints such as available training data and ground validation.
- What contextual or interpretive judgments are embedded in the analysis? Identify points where the analysis depends on assumptions (e.g., cropping calendars, recurring market days, typical land use practices) and what informs those assumptions.
- Do the proposed data sources, methods, or outputs raise risks for affected populations? Note safeguards for handling, storing, and sharing underlying data and derived outputs, including any aggregation or redaction.

Institutional capacity and constraints

- Do tools exist for this analysis, and are they fit for this application? Do we have the requisite skills, expertise, and computing resources in-house?
- What is the expected timeline for analysis and delivery? What are the resource requirements? Note any commercial data costs, computing requirements, specialized expertise, or partnerships needed to complete the analysis.
- Is there capacity and expertise for continued updates on the end product, or will it be static?
- What level of expertise is required to interpret the outputs responsibly?

Communication

- What formats are possible for outputs? For instance, could the team produce maps, tables, written analysis, dashboards, or other deliverables?
- How will limitations and uncertainty be communicated alongside results? Consider including plain-language summaries, confidence indicators, or caveats alongside outputs.
- Are there commercial or licensing restrictions on the imagery or derived products that affect how outputs can be shared?
- What ongoing technical support will be available? Identify how technical questions, requests for clarification, or follow-up analysis will be handled after delivery.

Appendix C: Select Case Studies by Application

Early Warning and Anticipatory Action

- Group on Earth Observations (GEO). "Integrating Earth Observations into the Formulation and Implementation of National Adaptation Plans: Agriculture and Food Security." NAP Central, 2022. <https://napcentral.org/supplementary-materials/147>.
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