Localized Food Insecurity Index: Understanding Cross Boundary Food Security At A Community Level

Table of Contents

Introduction

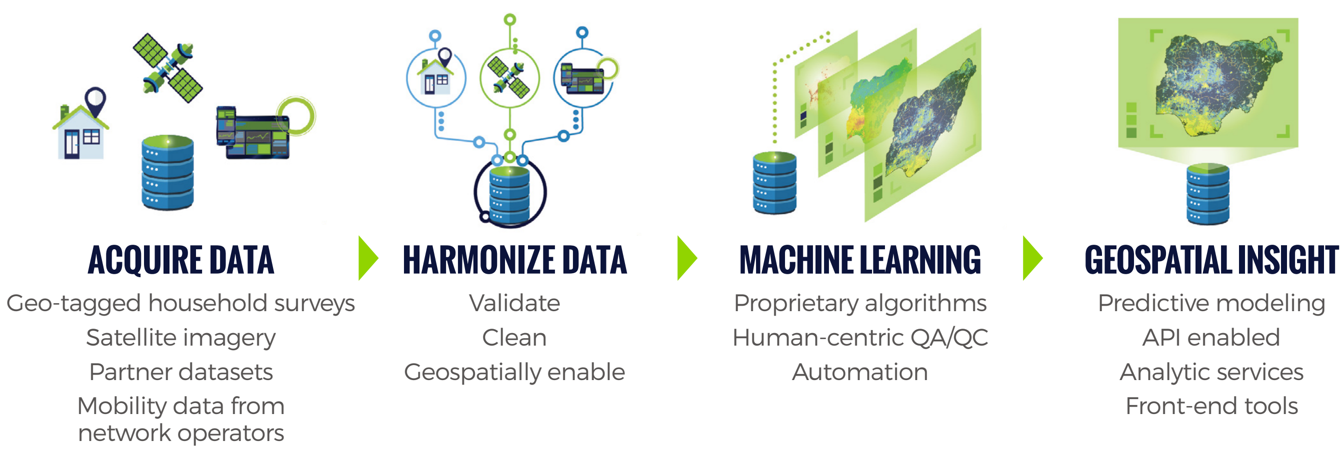
Governments around the world are scrambling to address the impending food crisis brought on by the coronavirus pandemic, one that the World Food Program estimates could almost *double the number* of people suffering acute hunger by the end of the year. Driven by a combination of economic downturns, price hikes, and trade restrictions, this worldwide food crisis is particularly acute in developing countries that were *already vulnerable*. Border closures, lockdowns, and curfews have dramatically *altered supply chains and livelihoods* in countries that rely heavily on labor-intensive activities like manual labor or subsistence farming. *Worldwide demand for oil and cash-crops has steeply declined* since the start of the pandemic—industries that account for much of the economic activity in many emerging economies. Taken together, these circumstances could result in acute hunger for millions of people.

Countries in Africa and southeast Asia are already experiencing pandemic-caused food shortages. In Nigeria, the number of undernourished people had already risen *180% in the last decade*, placing the country (pre-pandemic) in the top ten worst food crises in the world. Following COVID-19 lockdowns in Abuja, Lagos, and Ogun state, residents saw *food price increases up to 50%* as borders with Benin closed and local farmers faced roadblocks getting their food to markets. In Pakistan, rural food producing areas *like Sindh province* suffered a series of natural hazards and high rates of stunting and wasting before the pandemic. These communities have now been hit hard both by the virus itself, and its accompanying effects on food production, incomes, and trade.

Governments and development organizations need to take urgent and well-informed steps to mitigate the potential food security impacts of COVID-19. This paper introduces a new data tool—the Localized Food Insecurity Index—that will enable policymakers to anticipate and proactively address acute, pandemic-induced food insecurity around the world.

About the Localized Food Insecurity Index

For all of its data products, Fraym uses advanced ML to combine survey data and satellite imagery—using harmonized survey data to 'train' a series of models which use remote sensing data as inputs to calculate population characteristics with 1km² resolution. The end product is a consistent, geospatial 'surface' of local population characteristics that covers an entire country. Fraym's approach has been applied to produce dozens of socioeconomic, demographic, and behavioral indicators for countries across Africa, Asia, Eastern Europe, Latin America, and the Middle East.



1. See *World Food Program USA's worst food crises*

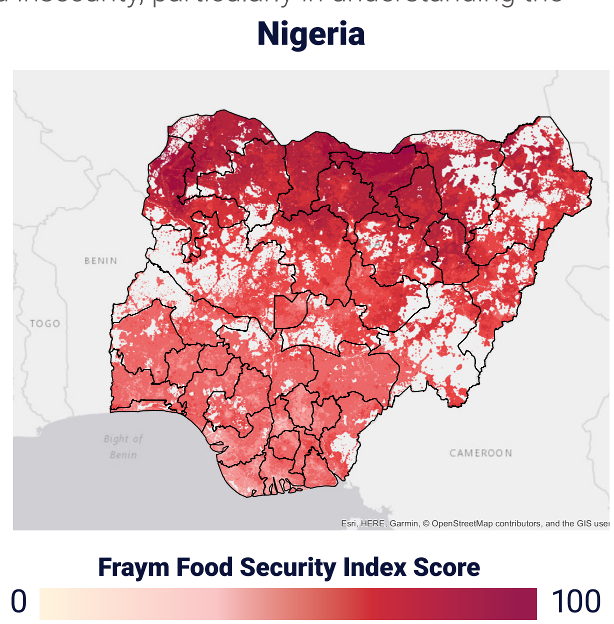
This unique geospatial data provides the information necessary to identify and target at-risk areas, assess their economic, health, nutrition, and social characteristics, and calculate their overall risk of food insecurity at a hyper-local level. Critically, this can typically be done without deploying additional data collection resources—including enumerators.

Using a series of population data layers, Fraym constructed a Localized Food Insecurity Index (LFII) adapted from components in the International Food Policy Research Institute's (IFPRI) Global Hunger Index (GHI). Policymakers have relied upon the GHI since 2006 for identifying food security threats and vulnerabilities at the national level. **Fraym's goal was to make the same insight available for decision-makers at the hyper-local level**—and to do this without risking the health and safety of enumerators in the COVID-19 environment.

The resulting **Localized Food Insecurity Index (LFII)** is a community-specific targeting tool that maps and quantifies food insecurity. With this information, efforts to address food security and its downstream effects can be designed and implemented at the level of individual communities, instead of a country- or regional-level. Potential applications include:

- Illustrating areas at greatest risk for food shortages to inform humanitarian and development assistance planning and resource allocation
- Anticipating likely economic consequences of food insecurity, particularly in understanding the least resilient communities
- Modeling the likelihood of unrest or extremist activity as a result of food insecurity, providing critical indications and warnings for local governments and development organizations delivering services in these areas

Here, we outline two potential use cases for Fraym's LFII. For this paper, we produced data and analysis for Nigeria and Pakistan, but the Index can be scaled to nearly any country of interest.



Gray areas in each country are 1x1 square kilometer grids with less than 30 people.

Figure 1: Example of Fraym Localized Food Insecurity Index for Nigeria

Rank	State	LFII Score
1	Jigawa	76
2	Sokoto	73
3	Katsina	73
4	Kebbi	71
5	Yobe	71
6	Zamfara	69
7	Bauchi	67
8	Gombe	65
9	Kano	65
10	Borno	65
11	Kaduna	58
12	Adamawa	57
13	Taraba	54
14	Plateau	53
15	Niger	52
16	Nasarawa	50
17	Kwara	46
18	Kogi	46
19	Cross River	45
20	Benue	44
21	Oyo	43
22	Abia	43
23	Ekiti	42
24	Akwa Ibom	42
25	Ebonyi	41
26	Ondo	41
27	Imo	41
28	Edo	41
29	FCT	41
30	Osun	41
31	Ogun	40
32	Delta	39
33	Rivers	38
34	Bayelsa	37
35	Lagos	37
36	Enugu	35
37	Anambra	33

Table 1: State by State Ranking based on the LFII Score

Application One: Mapping Food Needs

Many urban and rural markets around the world are absorbing dual food supply and demand shocks due to the COVID-19 pandemic. The implications of these shocks are particularly acute across much of the developing world—and will likely lead to widespread hunger. For example, food shocks in Nigeria threaten to exacerbate the food security circumstances across the country. In May 2020, President Buhari announced Nigeria had *'no more money'* to pay for rice imports, and with local production delayed or adversely affected by border closures, the country faces an impending rice shortage. In cases like this, how can the Fraym Localized Food Insecurity Index help decision-makers target humanitarian relief for maximum effect?

It is no surprise that the Famine Early Warning System Network (FEWS NET) projects that parts of Zamfara, Sokoto, and Katsina states will move from phase two to three (out of five), or to the 'crisis' stage, between June and September 2020 (see Figure 2). All three states rely heavily rice production for food and income. But effective interventions in these states will demand localized insight on at-risk communities and their unique characteristics and needs. To do this, we can leverage Fraym's LFII and examine variation between communities.

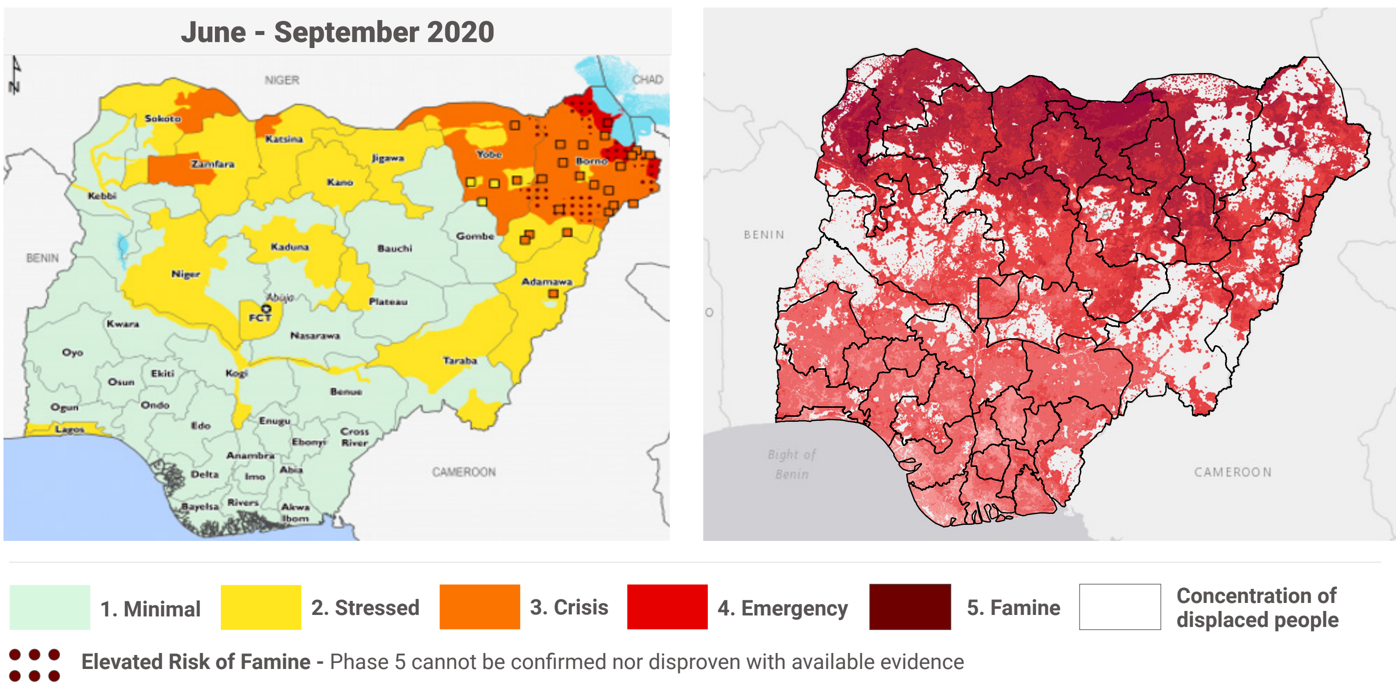


Figure 2: Side by side comparison of FEWS NET IPC Food Security Projections and Fraym LFII

2. Sess Phase 3 of FEWS is defined as 'Have food consumption gaps that are reflected by high or above-usual acute malnutrition' or 'are marginally able to meet minimum food needs but only by depleting essential livelihood assets or through crisis-coping strategies'. *https://fews.net/west-africa/nigeria, https://fews.net/IPC*

3. *https://fews.net/sites/default/files/documents/reports/NG_LZ_2018.pdf*

4. The rise in rice prices increased by more than 10 percent across sources (locally or imported), and distribution channels (retail and wholesale channels). Prices were obtained from the World Food Prices database.

For example, in Zamfara state, we see that communities lying between Talata Mafara and Bakura local government areas score between 80 and 85 on the Index, or 10 to 15 points higher than the state average of 69 (see Figure 3). Coupled with the fact that rice prices have risen more than 15 percent between March and June 2020 in Zamfara state, households in these communities will have their purchasing power greatly diminished and their food supply further stretched. On the supply side, import restrictions have *prevented farmers from obtaining inputs*, such as fertilizer and seeds, and beginning their planting seasons. Concurrently, border closures and lockdowns have prevented food from reaching local markets.

According to Fraym data, in Bakura and Talata Mafara alone, **100,000 people are living in households that rely on agricultural enterprises as their primary source of income**—households without adequate agricultural inputs will likely experience food shortages in the coming months. Further, with tensions escalating due to *farmer-herder conflicts and increasing infiltration from Islamists extremists in North West Nigeria*, this instability will only serve to increasingly disrupt planting and harvesting cycles. Securing market access and providing food aid relief to households in areas like Bakura and Talata Mafara will be critical to reducing the destructive impact that these households face from demand and supply shocks in northeast Nigeria. Similarly, decision-makers can use the Fraym LFII to map and quantify needs and inform food distribution and nutrition programming across Nigeria and in all at-risk countries across Africa and around the world.

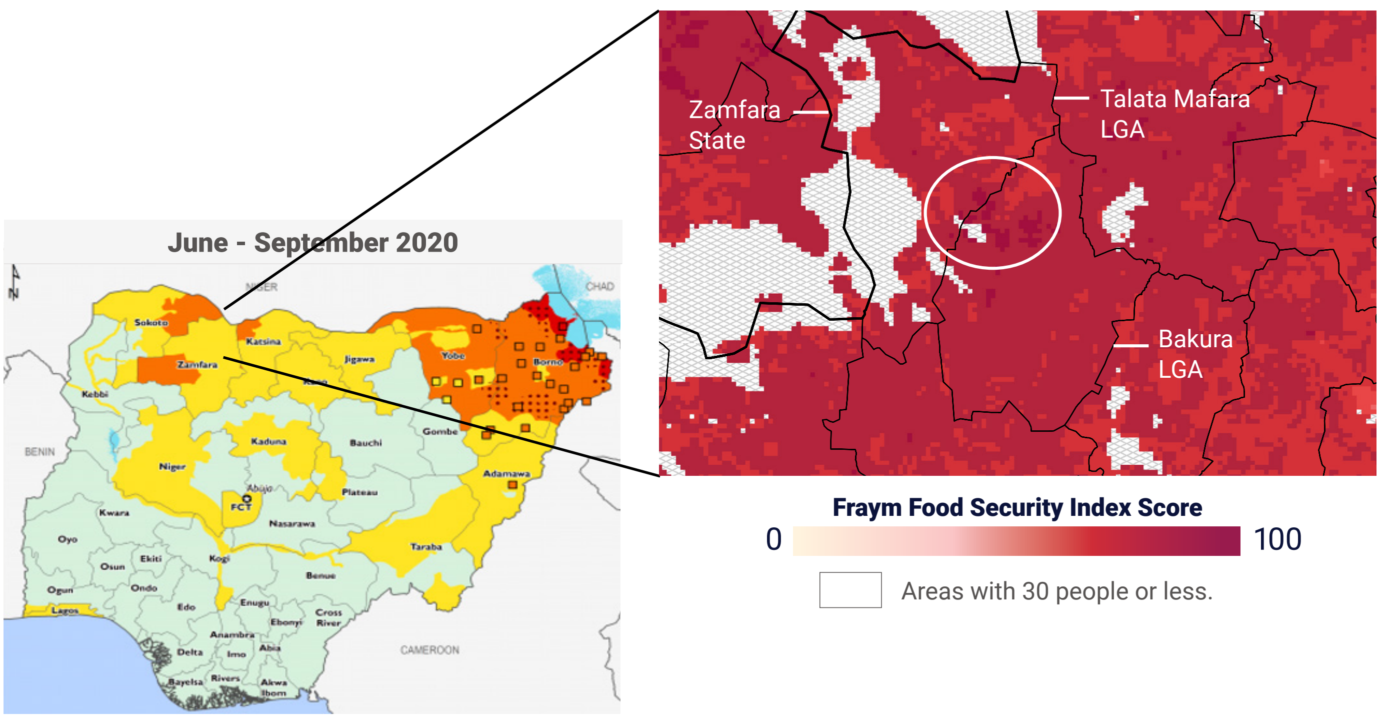


Figure 3: LFII demonstrates food insecurity across state boundaries

2. Sess Phase 3 of FEWS is defined as 'Have food consumption gaps that are reflected by high or above-usual acute malnutrition' or 'are marginally able to meet minimum food needs but only by depleting essential livelihood assets or through crisis-coping strategies'. *https://fews.net/west-africa/nigeria, https://fews.net/IPC*

3. *https://fews.net/sites/default/files/documents/reports/NG_LZ_2018.pdf*

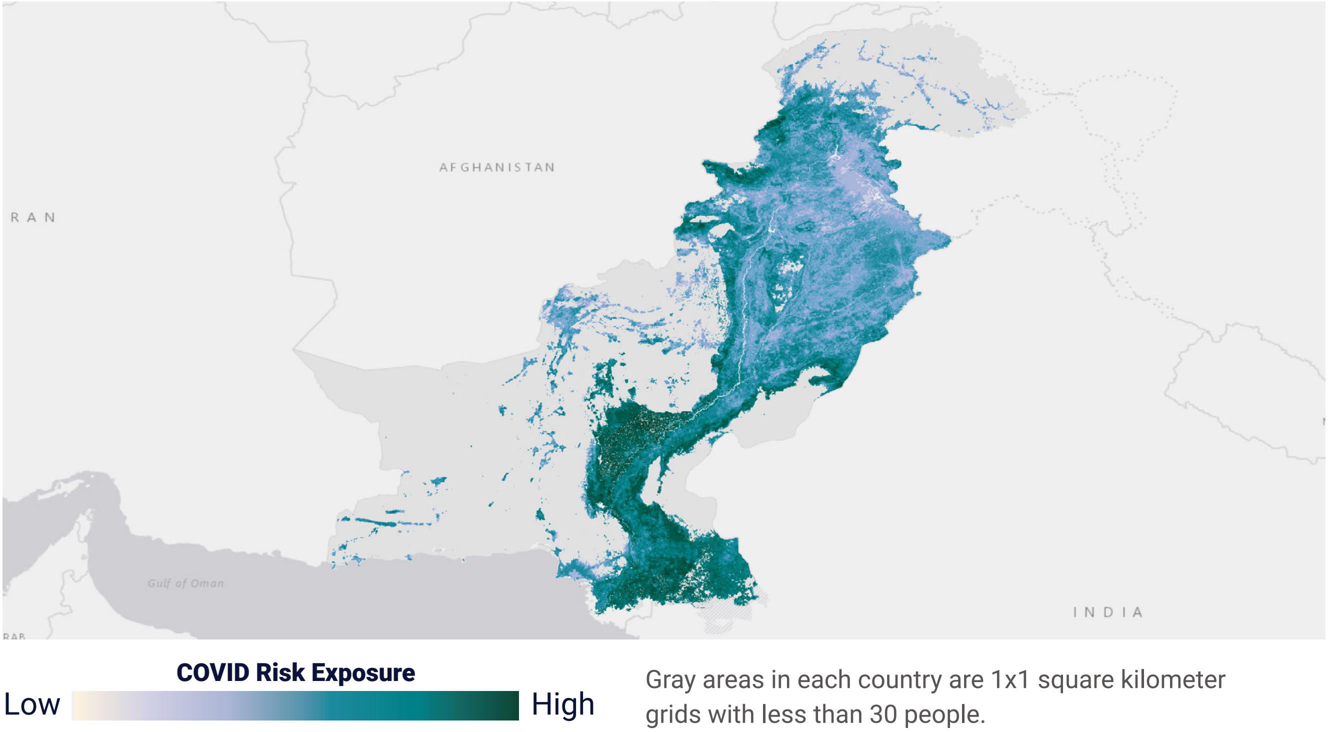
4. The rise in rice prices increased by more than 10 percent across sources (locally or imported), and distribution channels (retail and wholesale channels). Prices were obtained from the World Food Prices database.

Application Two: Tailoring Local Inventions

In Pakistan, Fraym's LFII provides similar guidance for mitigating food insecurity in the country's hardest-hit provinces. A *recent IMF report* projects a sharp increase in poverty in Pakistan as a result of COVID-19's economic impact, a trend that could push those already food insecure into desperate situations. Paired with Fraym estimates of COVID-19 risk factors, **the LFII highlights priority areas for response with community-level precision.**

Punjab, Pakistan's most populous province, has over 22 million people in communities at the highest risk level for COVID-19 exposure—meaning 22 million people are already experiencing a high number of COVID-19 cases and are highly vulnerable to contracting the virus due to lifestyle factors that are both within and out of their control. *A leaked letter from the World Health Organization* warned that Punjab's health system is near collapse, which will only be compounded by additional COVID-19 cases. Sindh province currently has the highest number of cases in Pakistan, over *900 of which are among children under 10*. This province also has some of the highest rates of childhood stunting in the country, with Fraym data showing stunting rates of 46%. For each of these priority areas, Fraym indices and community-level data reveal where and who should be prioritized for social safety net and food-security protection investments within Punjab and Sindh.

As the province with the most cases, communities in rural Sindh will require support to ensure already at risk populations maintain or improve food security as the pandemic disrupts agricultural livelihoods.



Gray areas in each country are 1x1 square kilometer grids with less than 30 people.

Figure 4: COVID-19 Exposure Risk in Pakistan

In this province, the Food and Agriculture Organization is *already exploring investments in livestock ownership and sanitation* that could have complementary benefits for combatting COVID-19's impact. According to Fraym data, 43% of households in Sindh province own livestock, representing a major source of income and wealth, while almost 65% lack access to piped water—essential for both maintaining livestock and agricultural production as well as preventing the spread of COVID-19. Viewing Fraym's LFII and exposure risk heatmaps, rural communities surrounding Jacobabad 'pop' as areas with particularly high need for similar investments in sanitation.

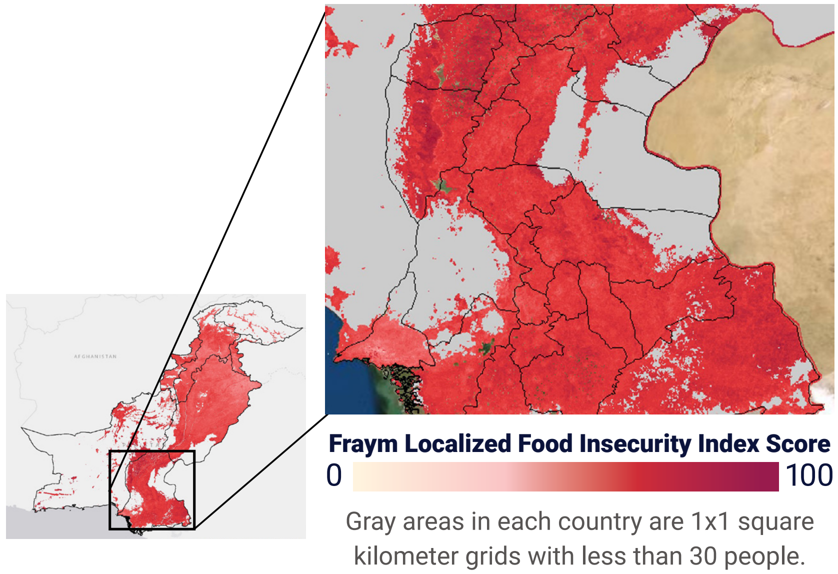


Figure 5: Food Insecurity in the Sindh Province

Response efforts differ dramatically in the industrialized and urban Punjab province. Here, Fraym data shows 36% of the population lives in urban areas, increasing both risk of exposure and loss of income from possible lockdowns. Responding to pressure from the World Health Organization, the *Punjab government imposed two-week lockdowns* of certain areas of Lahore. Fraym data shows that 2 in 5 adults (people between 15 and 49) in Lahore are not employed, or 2.3 million people. Among the 3 million adults that are employed, 40 percent, or 1.2 million people, are employed in occupations that they would continue to do despite a pandemic in order to maintain a source of income, otherwise referred to as 'essential occupations' (retail, construction, and transportation, etc.). Cash transfer programs to areas with higher concentrations of workers who desperately need their occupations may mitigate the loss of income during current and future city-wide lockdowns. Fraym data identifies these populations with neighborhood-level precision, enabling targeted and efficient response planning to alleviate food insecurity in urban areas.

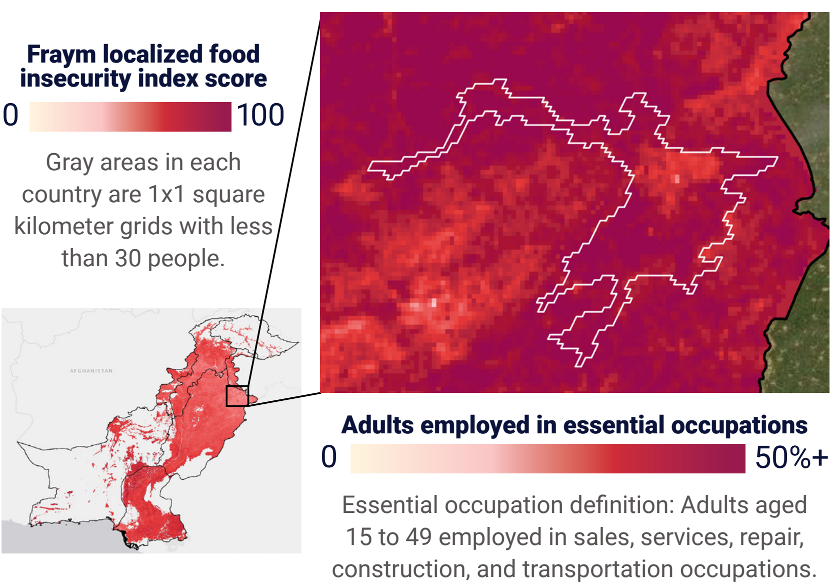


Figure 6: Essential occupations in Lahore, Punjab

* the granularity of the data may make this image look blurry

Annex One

Fraym produced data layers covering each of the four components at the 1km2 level with only modest definitional adjustments listed in Table 2. Next, following the longstanding GHI approach, each data layer component was divided by the highest observed levels of each indicator (from 1988 to 2013) and multiplied by one hundred to obtain a standardized score for each component (see Figure 6). These scores were weighted accordingly and then aggregated to produce a final score (see Figure 7).

Components	Definition	2018 Highest Observed Level
Child Mortality (CM)	Mortality rate of children under the age of five.	35%
Child Stunting (CST)	Share of children under the age of five who are stunted: defined as two standard deviations from median height for age of reference population, (reflecting chronic under nutrition);	70%
Child Wasting (CWA)	Share of children under the age of five who are wasted: defined as two standard deviations from median weight for height of reference population, (reflecting acute under nutrition)	30%
Undernourishment (PUN)	Share of the population that is undernourished: defined as caloric intake that is insufficient to meet the minimum energy requirements necessary for a given individual. Please see Fraym's technical methodology note for further details on this calculation.	80%

Table 2: Localized Food Insecurity Index Components
Source: IFPRI, Global Hunger Index.

$$\text{Component Standardization} = \frac{\text{Component}}{\text{Highest Observed Level of Component x 100}}$$

Figure 7: Standardization formula

$$\text{Food Security Index Score} = \tfrac{1}{3}\,\text{Standardized CM} + \tfrac{1}{3}\,\text{Standardized PUN} + \tfrac{1}{6}\,\text{Standardized CWA} + \tfrac{1}{6}\,\text{Standardized CST}$$

Figure 8: Localized Food Insecurity Index formula

POC

Melissa Persaud
551.427.1628
m.persaud@fraym.io

Address: 3101 Wilson Blvd., Suite 300, Arlington, VA 22201
Cage Code: 7QVL1
DUNS: 080416518
US Small Business