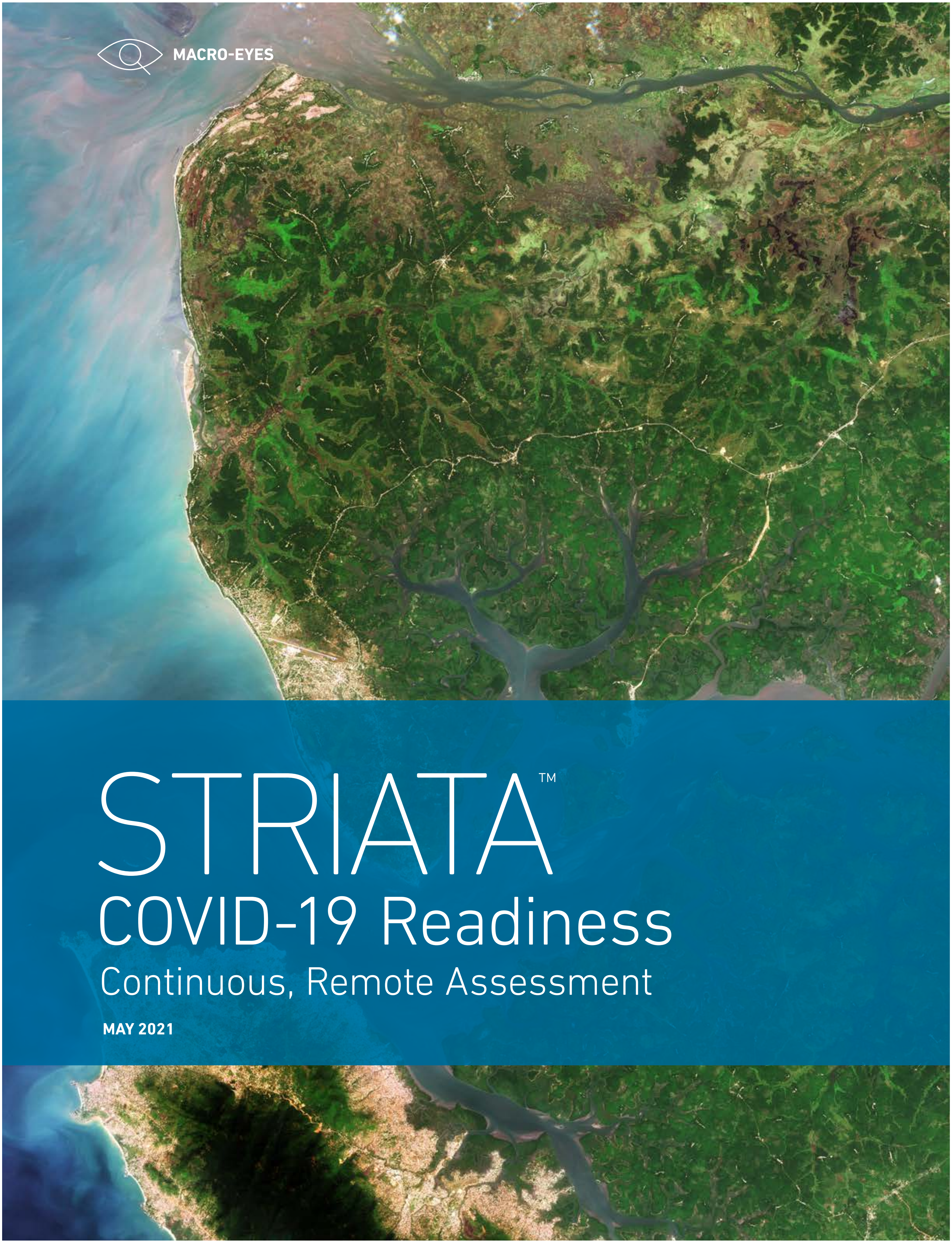

MACRO-EYES

STRIATA™

COVID-19 Readiness

Continuous, Remote Assessment

MAY 2021

INTRODUCTION

METHODOLOGY

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Executive Summary

The goal of Macro-Eyes is to enable healthcare systems to deliver more care with existing resources; we believe this makes health systems more resilient. The scarcer the resources, the greater the need to deploy these resources strategically. This is critical for the country of Sierra Leone.

According to the World Health Organization (WHO), Sierra Leone's health system faces challenges due to a heavy disease burden, chronic underfunding, and vastly insufficient volume and skewed distribution of skilled human resources for health. Capacity, in terms of numbers, skills and distribution of human resources is one of the main barriers to improving health care1. The Ebola outbreak and the COVID-19 pandemic created further challenges for achieving its development goals. But their experience from the outbreak made them aggressive advocates of early and innovative action in times of crisis — a global leader in pandemic response.

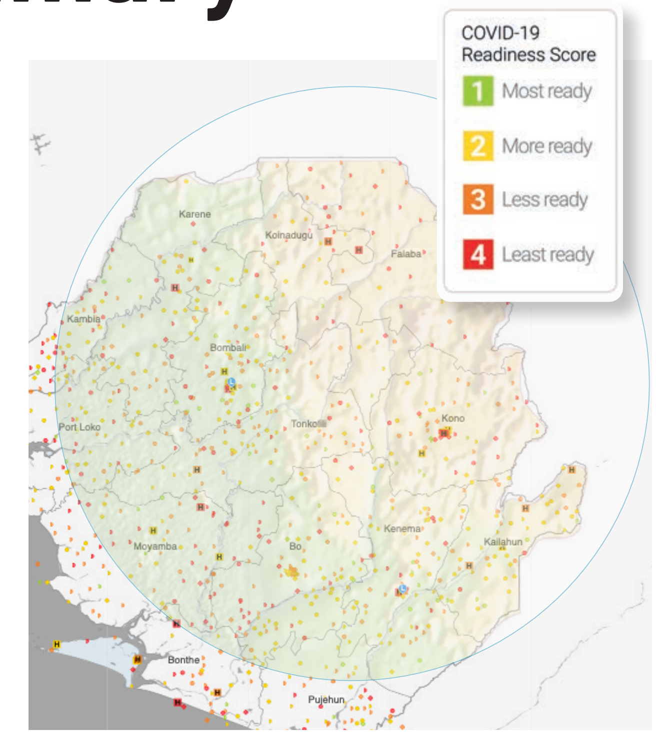


Fig. 1. Introducing Striata, a product running Macro-Eyes AI that supports improvements in the delivery of health care through multi-dimensional harvest of data, imagery and predictive analysis.

Macro-Eyes developed Striata, a product running core Macro-Eyes artificial intelligence (AI), to continuously assess the national health system and generate health facility readiness scores for COVID-19 response. Through the use of multi-dimensional data (health data to satellite imagery to information scraped from the public internet including news) Striata generates a real time "resiliency index" for the national which highlights geographic areas of strength and opportunity. The Macro-Eyes product Striata helps Sierra Leone leaders assess available capacity of health facilities and identify where and when well-defined resources will save the most lives (Figure 1).

Over the course of five months, Macro-Eyes worked with Ministry leaders at the Directorate of Science, Technology and Innovation (DSTI) and the Ministry of Health and Sanitation (MOHS) to understand the operating environment, access data for Striata, explain the use and design of AI, and initiate a co-creation process to build the technology for COVID-19. A MOU was signed between Macro-Eyes and the MOHS on December 15, 2020 to further develop Striata for the COVID-19 response and other health areas.

Striata was initially built on data focused on the geographic region of Sierra Leone, while addressing a global need. As a product that rests on the capability to learn from images taken at ground level and from the sky, numbers, and natural language — Striata is fundamentally scalable. Striata also learns from proxy data. We see proxy data as an alternate view on ground truth that may be described explicitly elsewhere. For example, Macro-Eyes AI used publicly available data describing the condition of schools as a way to predict (with significant accuracy) whether a health facility had running water.

Butorides striata

To invest for impact, you must know what's in place. To improve health systems, you must be able to measure them. Health systems globally will benefit from the capability to assess infrastructure and capacity in real-time, continuously learning.

1 https://apps.who.int/iris/bitstream/handle/10665/136868/ccsbrief_sle_en.pdf?sequence=1 (May 2018)

Macro-Eyes by the numbers

1088 **COVID-19 readiness predictions**
with Striata for health facilities throughout Sierra Leone at three levels of readiness

849 **geo-locations verified**
for Sierra Leone health facilities

600+ **variables analyzed**
for developing COVID-19 readiness scores via Striata

16 **solar arrays identified**
with satellite imagery at health facilities throughout Sierra Leone

<15 **% error rate for prediction**
of COVID-19 readiness scores per health facility in Sierra Leone

8 **types of data utilized**
for Striata to generate the COVID-19 readiness scores

3 **phenotypes developed**
to further define the COVID-19 readiness scores into most-least ready

Introduction

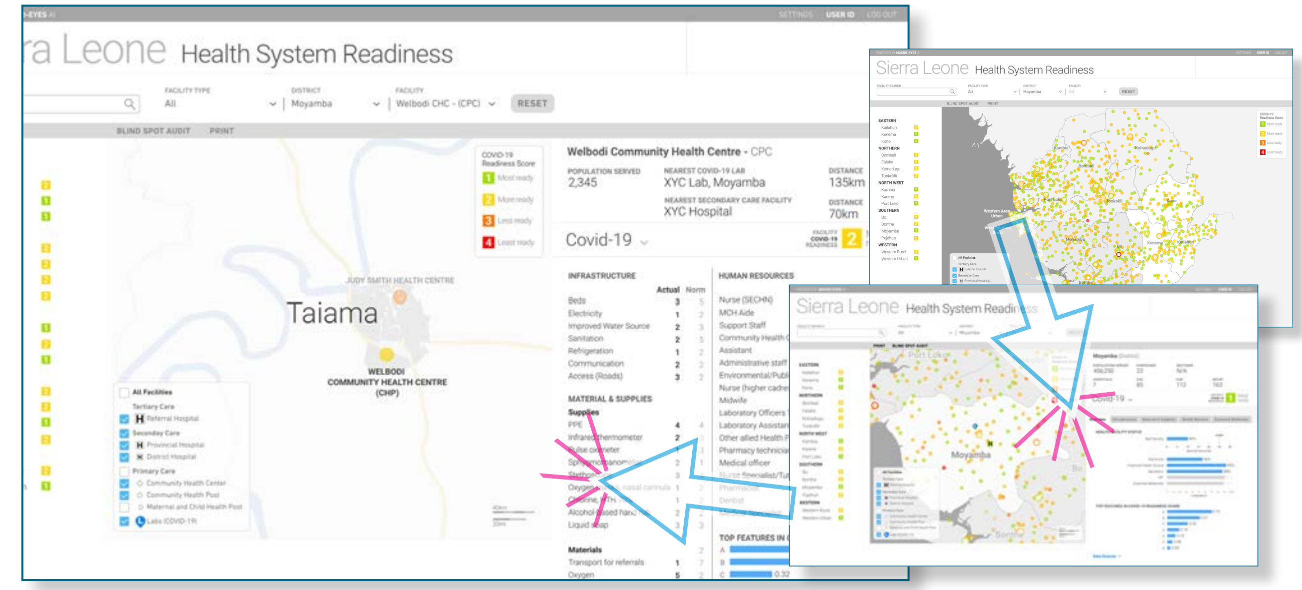


Fig. 2. The Striata Interface at three levels of granularity

A Question of Health Facility Capacity

Health systems, governments and multilateral institutions rely on assessments — primarily surveys — to provide insight into capacity and the quality of care.

Traditional health system assessments are costly, require time and focus to complete, and result in a frozen data frame — already outdated by the time it's published. Macro-Eyes machine learning (ML) technology, Striata, transforms the way health system data is activated and understood — offering the opportunity to make health system assessments continuous and significantly more data-driven, generating near real-time views into the state of infrastructure. Striata can be used for planning, resource allocation and policy development. It is even more critical during a health emergency when resources become more constrained and knowledge about a health system's capacity to respond on a day-to-day or even hour-by-hour basis can mean the difference between life and death.

Macro-Eyes built the Striata ML system to track and predict changes in capacity at the facility level, generating a real-time view into health facilities, and measuring capacity to respond to COVID-19 both at district and facility level (Figure 2). The product is being implemented in Sierra Leone, but relies on infrastructure, systems, and a data visualization framework that is widely generalizable. By combining publicly available data, facility-specific information[2] and satellite imagery, Macro-Eyes AI can accurately determine a facility's readiness to effectively care for COVID-19 patients and continue to deliver essential medical care. By generating a "resiliency index" for the health system as a whole, the Macro-Eyes product helps Sierra Leone leaders assess available capacity of health facilities and identify where and when well-defined resources will save the most lives.

Stakeholders in Sierra Leone came to the consensus that a system collating data sources — and ML interwoven throughout to fill gaps and clarify errors — could significantly support the COVID-19 response. Macro-Eyes is working with a MOHS led technical working group to learn more from the outputs generated to date and to build local capacity to use the ML system to understand and act upon the insight into health system readiness. Additionally, the MOHS and DSTI have each nominated a person to serve as AI Tech Representative who will work closer with the Macro-Eyes Applied AI Team to understand in depth how Macro-Eyes generates predictive analytics for Sierra Leone. These positions were created to support the Ministry's request to foster local capacity for utilization of AI technologies.

2 2017 SARA Plus Survey raw data, MOHS HFA 2020 for 130 health facilities in Sierra Leone, all health facility geo-coordinates from Statistics SL

Background

In August 2020, the Sierra Leone Directorate of Science, Technology, and Innovation (DSTI) formally partnered with Macro-Eyes, Dimagi and Living Goods to support the Government of Sierra Leone (GoSL) to identify, design, demonstrate and sustainably scale digital health solutions for the COVID-19 response. As part of this response, Macro-Eyes worked closely with the Presidential Task Force on COVID-19 Information, Communication and Technology (ICT) pillar and the Ministry of Health and Sanitation (MOHS) to integrate ML into existing systems including efforts led by the National COVID-19 Emergency Response Centre (NaCOVERC).

Over the course of five months (August through December 2020), Macro-Eyes engaged with key stakeholders and Ministry leaders in Sierra Leone to obtain data or the ML system; built and refined ML models to understand ground-truth for health facilities; and built an intelligent health systems index used by Ministry leaders to support the COVID-19 response.

Building the ML System to Predict COVID-19 Readiness

Striata deploys both unsupervised and supervised ML to predict COVID-19 readiness for each health facility in Sierra Leone.

Data sources included Sierra Leone 2017 Service Availability and Readiness Assessment (SARA) Plus Survey; Sierra Leone MOHS COVID-19 health facility assessment (HFA) survey (May 2020); news and social media scraped from the public internet;[3] Google Earth Pro; and high-resolution satellite imagery from MAXAR. Satellite imagery was used to either confirm or correct the locations of health facilities. Web scraped data from recent news articles, together with Google Earth Pro, pinpointed the nearest COVID-19 testing laboratory for each health facility.

The 2017 SARA surveyed 1,200+ health facilities across ~600 variables. Some broad categories of variables include: infrastructure details (e.g., inpatients beds, maternity beds, access to clean running water); human resources (e.g., number of trained nurses, community medical officers); and power supply details. Additionally, the recent MOHS COVID-19 HFA includes updated health facility data for approximately 10 percent of all Sierra Leone health facilities and calculated COVID-19 readiness scores for these facilities. There are 18 variables (Appendix Table 1), including facility name and type, shared across the datasets. Striata aims at predicting and then binning COVID-19 readiness scores as defined by MOHS and clinically verified by intensivist Dr. Eoin West.[4]

Supervised Learning

Macro-Eyes used 18 shared variables across the two datasets to predict COVID-19 readiness as defined by MOHS. For supervised ML, a random forest regressor was used to model and predict. The majority of the data [75%] was used to train the model, 10% to fine tune the model hyper-parameters and a final 15% of the data was retained to evaluate model performance, measured in terms of Fraction Error (F.E.). FE calculates the difference between actual and predicted COVID-19 readiness scores and is expressed as a fraction of the actual COVID-19 score. On average, the Macro-Eyes model performs at an FE of 0.15 (or 15% error). FE was calculated for health facilities in data not "seen" by the model to avoid bias, and the values were extrapolated for each bin. The FE will continue to improve and Macro-Eyes anticipates another tranche of data from the MOHS by the end of December 2020[5] to significantly improve the foundational model discussed here.

3 Macro-Eyes derived the latitudes and longitudes for Sierra Leone's 6 COVID-19 labs from news articles (Sept 2020) — the presence of the labs was readily available or known prior from data shared from the GoSL. https://reliefweb.int/report/sierra-leone/new-covid-19-testing-laboratory-commissioned-rural-sierra-leone-supported-who

4 Dr. West is a pulmonologist/intensivist, researcher, and educator at the University of Washington. He sees patients in the Chest Clinic and in the Intensive Care Units at Harborview Medical Center. Dr. West's research focuses on lung infections and sepsis. He directs the UW's INTERSECT initiative, a program that focuses on lung disease and critical illness in the context of global health.

5 Data anticipated from the MOHS will include the master health facility list, DHIS2 indicators, DHS 2019 raw data, cold chain map and more up to date human resource data.

Methodology

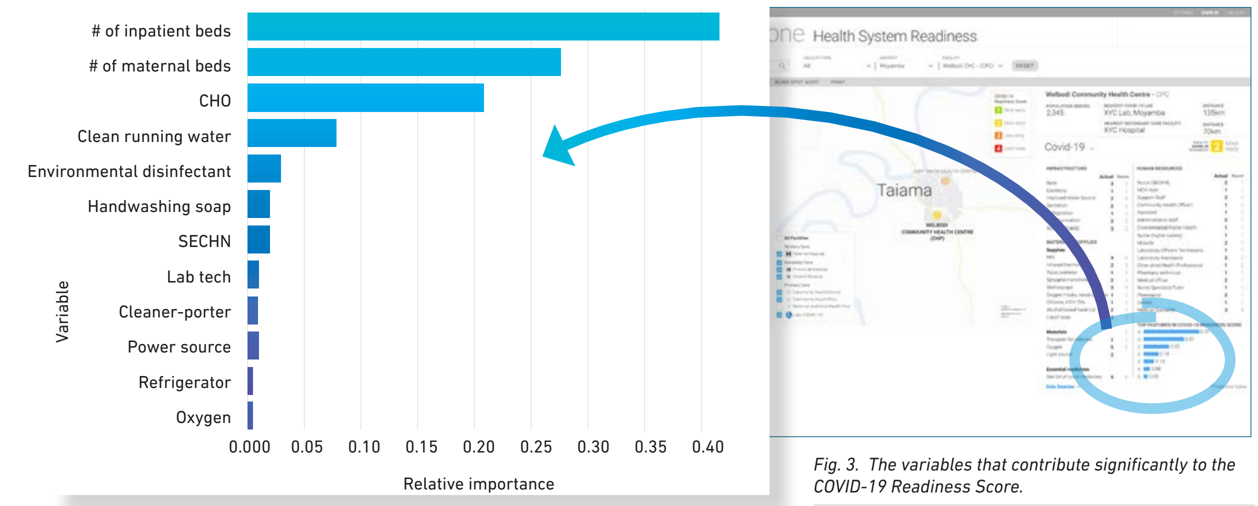


Fig. 3. The variables that contribute significantly to the COVID-19 Readiness Score.

The ML model calculates variable importance (Figure 3). Variable importance helps Ministry leaders and health personnel understand the elements that drive the COVID-19 readiness score to the greatest degree. The most significant variables include the number of beds, availability of environmental disinfectant, and trained health personnel.

Unsupervised Learning; Phenotyping Health Facilities

Macro-Eyes applied unsupervised learning (carefully constructing graph neural networks) to machine-learn groups of health facilities that share common characteristics. Unsupervised ML allows the data to auto-cluster, removing the bias that results from searching for a specific outcome or output. This approach helped Macro-Eyes identify phenotypes (data-driven, dynamic personas) for health facilities in Sierra Leone. The phenotypes enhanced and validated the consolidation of the COVID-19 readiness scores into four categories from the "most" to the "least" COVID-19 ready.

Graph neural networks are an extremely powerful, and equally complex to use, technology that allows for capturing rich spatial and temporal relationships in data that may otherwise be lost in other forms of analysis.[6]

Macro-Eyes identified three phenotypes for health facilities in Sierra Leone with distinct performance characteristics: 1) high performance; 2) middle performance; 3) low performance. Data anticipated from the MOHS will include the master health facility list, DHIS2 indicators, DHS 2019 raw data, cold chain map and more up-to-date human resource data performance (Figure 4). These divisions reflect the 2017 SARA Survey data auto-clustered across >1,000 dimensions. Facility type was varied across these clusters (i.e., hospitals were not generally aligned with one phenotype).

The most significant features of the three phenotypes were used to further understand defining characteristics: adolescent health

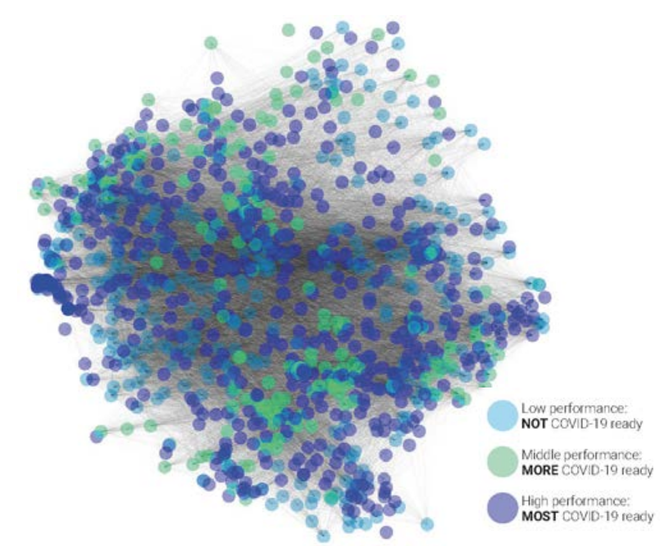


Fig. 4. Developing health facility phenotypes for Sierra Leone through unsupervised learning.

6 Macro-Eyes ML advisory board member Stefanie Jegelka is an expert on graph neural networks. Macro-Eyes Chief Scientist Suvrit Sra has also published on graph neural networks.

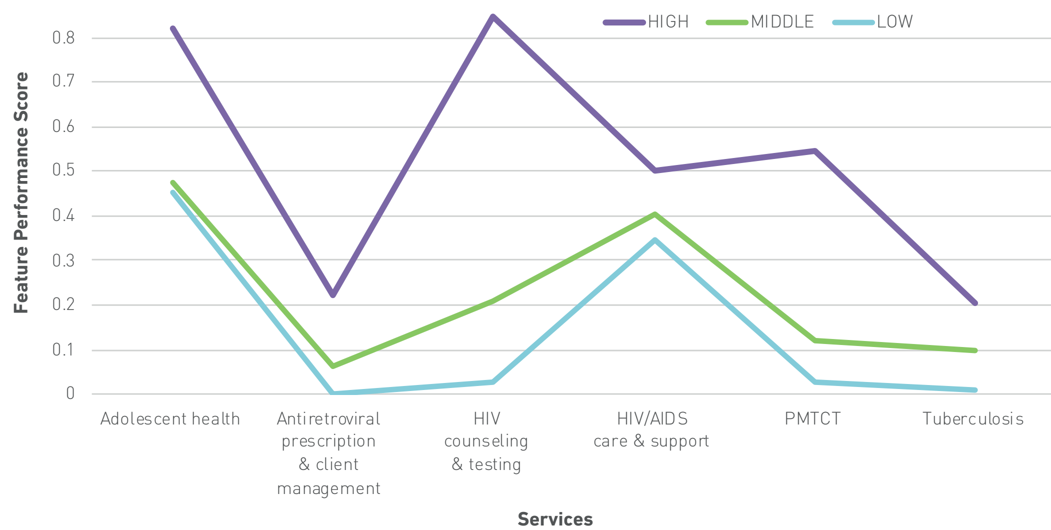


Fig. 5. Most Significant Features for Each Phenotype.

services, tuberculosis services, HIV counseling and testing services, HIV/AIDS care and support services, antiretroviral prescription and client management services, and PMTCT [prevention of mother-to-child transmission of HIV] services (Figure 5).

Further exploration of these elements is a worthy focus for the MOHS led technical working groups.

The initial unsupervised learning analysis was done on the 2017 SARA survey data. To test if the phenotypes kept similar characteristics in the MOHS HFA 2020 data, Macro-Eyes calculated the average COVID-19 readiness score of each group in MOHS HFA 2020 data (Figure 6).

This analysis validated the unsupervised learning by showing that the Macro-Eyes approach remotely generated facility classifications that correspond

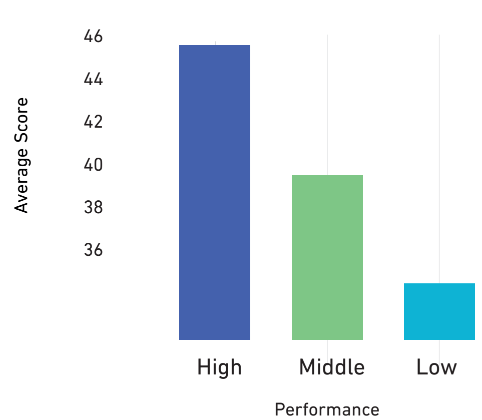


Fig. 6. Average COVID readiness score of facilities for each phenotype in recent MOHS Health Facility Assessment data (n=84).

with the outcomes of a traditional and resource-intensive assessment done by MOHS and Dimagi:

- *Facilities in a:* ***high*** *performing phenotype correspond to:* ***higher*** *COVID-19 readiness scores*
- *Facilities in a:* ***mid****-performance phenotype correspond to:* ***middle*** *COVID-19 readiness scores*
- *Facilities in a:* ***low*** *performing phenotype correspond to:* ***lower*** *COVID-19 readiness scores*

We compared results from the supervised learning predictions with the phenotypes defined by unsupervised learning to define 4 bins of COVID-19 readiness scores. Binning our results in this way strengthens the meaning of the health facility readiness scores for COVID-19, better reflecting relative readiness.

The Macro-Eyes approach to ML is always multi-modal, incorporating multiple dimensions of data to overcome the relative weakness in any single dataset and to incorporate a more complete crowd of points of view. By setting unsupervised and supervised learning against each other, we further strengthen the quality of the results — relying on multiple dimensions of very different data from different sources and analyzing that data in two very different ways. The correlation between bins [supervised learning] and clusters [unsupervised learning] was 0.71 (Spearman's coefficient). Spearman's correlation coefficient ranges -1 (inversely correlated) through 0 (no correlation) to a maximum of 1 (fully correlated). A correlation coefficient of 0.71 suggests a strong correlation.

More Insights to Improve COVID-19 Readiness Scores

Macro-Eyes provides additional machine learned insights to guide Ministry leaders on how to improve their COVID-19 readiness scores at health facility level. Users of Striata are clearly able to see what is going well at their health facilities in terms of COVID-19 preparedness and what is needed to improve their readiness scores (Figure 7). The machine learning team first computed average feature values of the most COVID-19 ready facilities for each district. Then, they subtracted the feature values of each, less COVID-19 ready facility from this average to understand what is needed to improve COVID-19 readiness scores. These additional insights are critical to supporting Ministry leaders in the moment when life-saving decisions are being made.

Satellite Imagery and Web Scraping[7]

Satellite imagery provides a continuous and unbiased means to monitor health facilities and update information about the facility's capacity to serve clients. Low-resolution imagery is widely available for the entire planet — the only truly democratized data sources on earth. Different indexes (i.e., vegetation, flood or burn indexes) reveal how health facility environments change over time.[8] High-resolution imagery reveals more detail about the infrastructure of health facilities (i.e., solar panels, facility footprint, wells, sanitation facilities). Satellite imagery can provide insights about all health facilities without the need for physical visits and allows the Ministry to see and document change over time more quickly.

In Sierra Leone, Macro-Eyes deployed an enhanced web scraping tool to verify anomalies seen in satellite imagery. Web scraping is a process by which researchers and organizations collect data from public websites. This process can be done manually — when you search Google you are effectively scraping the web — or automatically when a computer program crawls web pages using pre-defined logic and iterating queries based on that logic (Figure 8).

Web scraping can target text-based data or rich mediums like videos and images. Our web scraping activities were focused on identifying change at the level of an individual health facility and/or its operational environment. Sierra Leone has one of the lowest rates of internet penetration in the world and low adult literacy. In this context [fewer people posting to the public internet], the contribution of the web scraper to understanding health facilities speaks to the consistent value of learning from the public internet about change in health infrastructure and the "context for care"

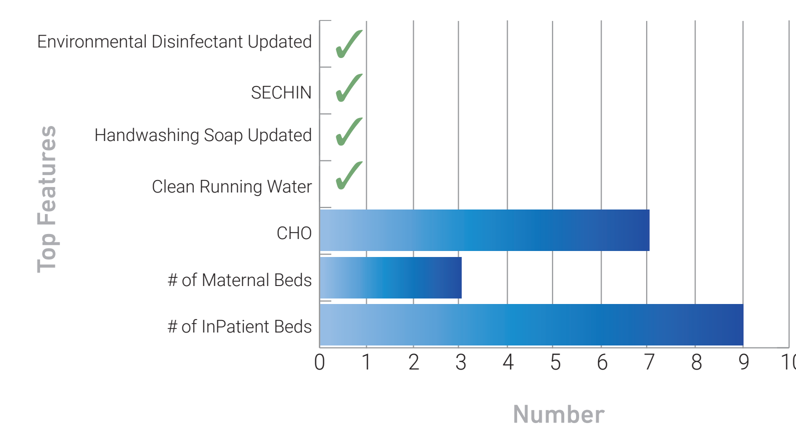


Fig. 7. Specific Health Facility (CHC) in Bo's Output Recommendations to Improve COVID-19 Readiness Score

7 Web scraping is used for the purpose of detecting changes at the level of individual health facilities and is not targeting human subjects. While scraping the public internet, we consider all the potential privacy and security implications involved. We are not scraping individual facebook or twitter profiles. We encode the post ID in our database for an additional layer of security.

8 The field of remote sensing uses indexes for clearer comparisons across space and time. For example: a vegetation index is a spectral transformation of two or more color bands to enhance the visibility of photosynthetic activity and canopy structural variation. The majority of satellite images are the aggregate of red, green, blue color components — think of the satellites as seeing solely in red, green, and blue. An index thus allows ML models to focus solely on shifts in vegetation, essentially removing the noise from other elements.

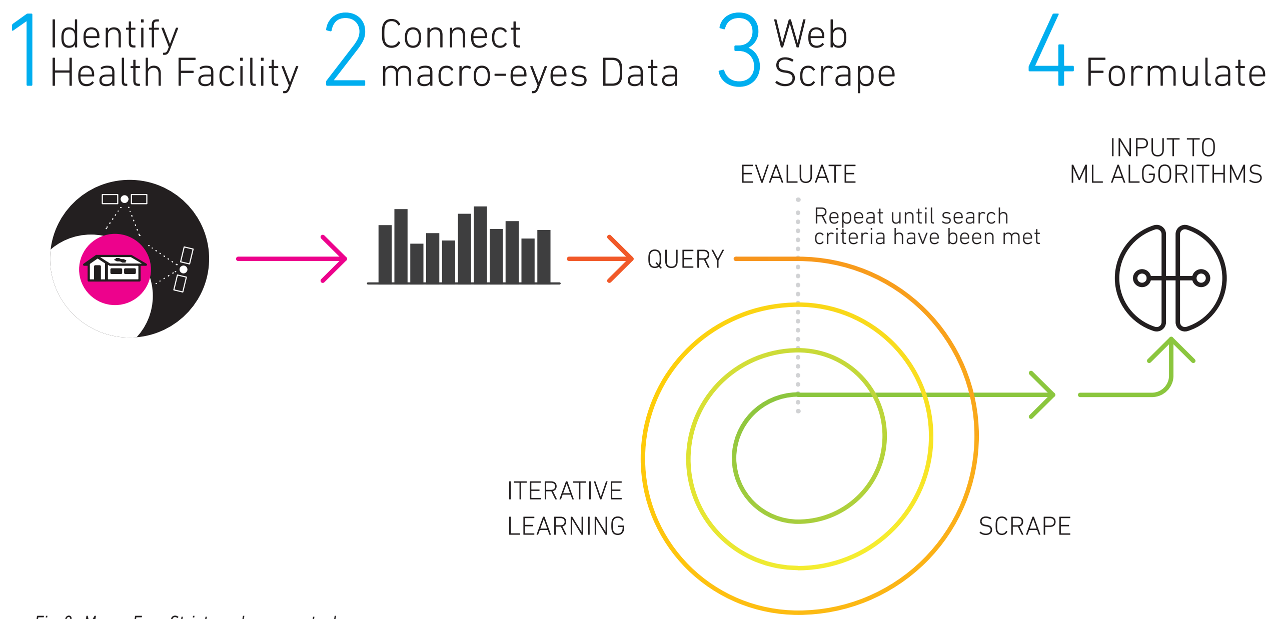


Fig. 8. Macro-Eyes Striata web scraper tool process map

Low-Resolution Satellite Imagery

Low-resolution satellite imagery contributed to understanding shocks to the health system. One approach was the analysis of Normalized Difference Vegetation Index (NDVI). NDVI compares the amount of vegetation found in satellite imagery (higher when there is more vegetation) and analyzes these changes to identify anomalies in the data, for example floods, landslides or wildfires. Figure 9 is an example of one health facility, Majihun Maternal and Child Health Post, where low-resolution imagery was captured on a monthly basis over a three-year period. Macro-Eyes averaged the NDVI over each patch and obtained a scalar time series of one value per month. This was repeated for over 1,000 health facilities in Sierra Leone to determine a mean NDVI (Figure 10). The instances of deviation from the mean are flagged as anomalies.

To learn more about anomalous events (Figure 12), an approximate date of the event was passed to an automated web scraper together with district and chiefdom names along with all the facilities that fall within the geographical boundaries. The Macro-Eyes web scraper built a set of queries with different keyword combinations to pass to a search engine [Google and Bing]. After each pass, information extraction algorithms were run and the resulting data was collected.

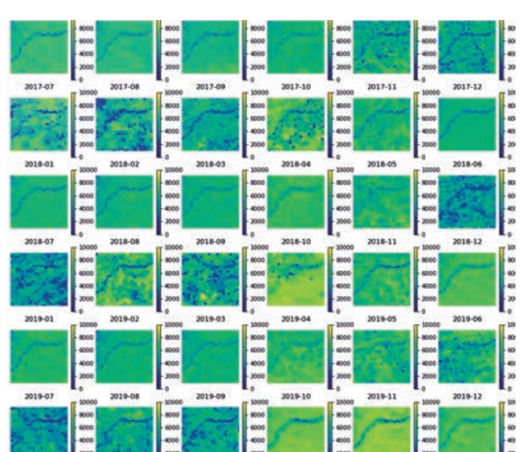


Fig. 9. Monthly NDVI index image of a 10km by 10km patch around one health facility from Jan 2017 to Dec 2019.

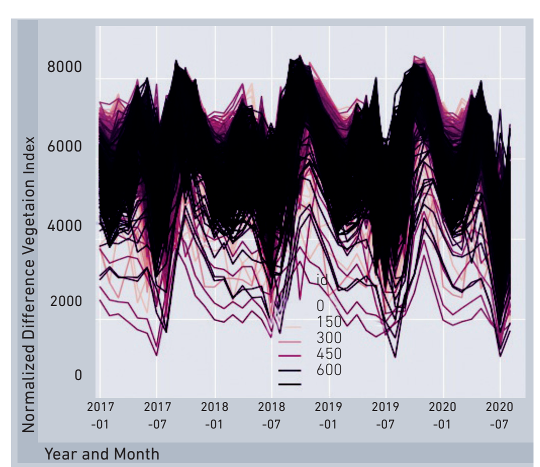


Fig. 10. Summary of one NDVI time series per health facility (n=584) in Sierra Leone over 44 months.

Macro-Eyes identified the following entities:

- *Non-GPE [Geographical Political Entity] locations;*
- *Mountain ranges, bodies of water;*
- *Buildings, airports, highways, bridges;*
- *Companies, agencies, institutions; and*
- *Countries, cities and states.*

The web scraper refines the search queries using extracted entities to narrow down the search. Query results are then grouped and further preprocessed to extract features that may be significant for Striata. In the case of Majihun Maternal and Child Health Post, unusual changes in vegetation were linked to flooding: confirmed by a news article, additional blog posts and a local tweet[9] about a nearby bridge collapse (Figure 11).

The example of Majihun shows how combining satellite imagery and web scraping can lead to pinpoint analysis of meaningful change in the environment of a health facility. Environmental change can impact the physical state of a health facility, its capability to deliver care, can determine access for healthcare workers or patients and can indicate vector-borne disease risk [Malaria]. These insights are fed into Striata to be considered in COVID-19 readiness scores and other indicators presented in the health system resilience index.

Fig. 11. Macro-Eyes connected NDVI anomaly with a web-scraped tweet about this major bridge collapse.

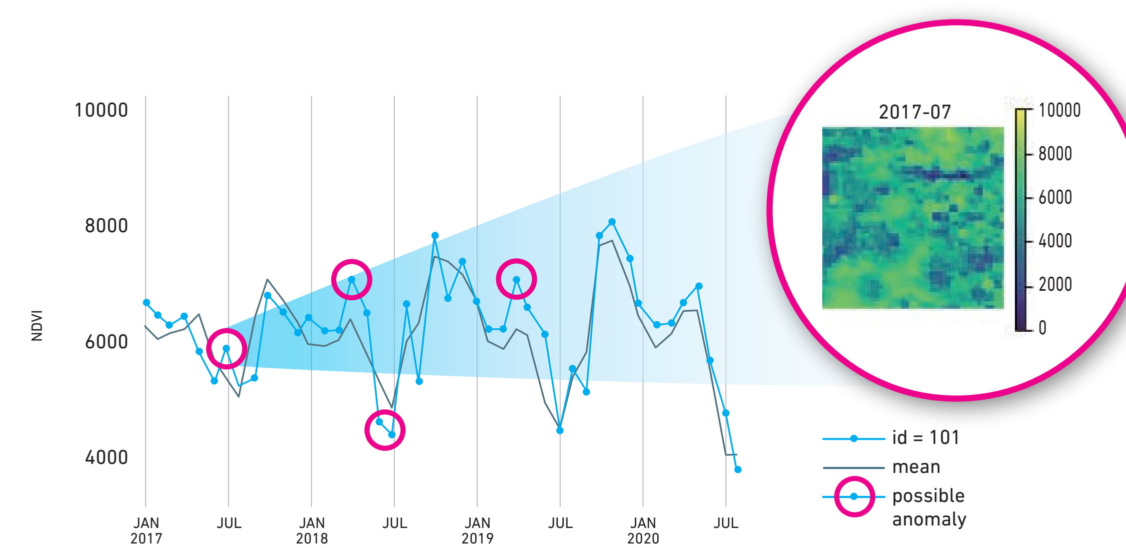


Fig. 12. Majihun MCHP NDVI time series compared to mean

9 **news article:** http://awokonewspaper.com/sierra-leone-news-flooding-in-kenema-2/
blog post: https://mountainwaves.blog/2020/09/10/road-linking-paki-masabong-and-safroko-limba-cut-off-by-floods/
local tweet: https://twitter.com/papa_bangura/status/1161971368000462850

Fig. 13. High-resolution satellite imagery of 2 health facilities (left, 2017, right 2020) helps Striata discover changes in solar electricity availability.

High-Resolution Satellite Imagery

Macro-Eyes used high-resolution satellite imagery to predict the state of electrification for health facilities across Sierra Leone. High resolution imagery is temporarily available without cost for 40% of Sierra Leone as part of MAXAR's Open Data platform. Macro-Eyes used a bespoke approach to determine if solar panels were visible in high-resolution satellite imagery. Preliminary results from current imaging show that over 16 health facilities which were listed as not having electricity in the 2017 SARA survey now have mini grids (36,000 watts). We are continuing to update the health data received from the GoSL with this new critical designation [access to electricity]. We hope to further update this technology in the next phase of this project. The global COVID-19 immunization effort poses an unprecedented cold-chain challenge; it is essential to be able to remotely assess access to electricity to determine where investment must be made for the safe storage of vaccines and which facilities should serve as immunization hubs.

The web scraping pipeline led to the discovery of the location of new COVID-19 laboratories in Sierra Leone. The web scraper retrieved a news article about the launch of a new lab opening in Sierra Leone and then derived latitudes and longitudes for 6 COVID-19 labs from news articles (Sept 2020). The Macro-Eyes dashboard now reflects the COVID-19 labs on the map and the distance of each health facility to the nearest COVID-19 lab.

Benchmarking Striata

Striata learns continuously and does not rely on self-reported data. To date, lengthy and expensive assessments and surveys are the only way for country leaders and health practitioners to measure their health systems. Globally, surveying efforts have struggled with the issue of non-response (Figure 13). We want to be clear that we are not advocating for eliminating surveys; Striata benefited from survey data. When surveying is paired with ML, faster, far less expensive surveys can be done in an extremely targeted manner — focusing in on the handful of points on the map where there is high uncertainty. Most importantly, the results can then be scaled to provide greater clarity for similar sites and conditions across the map.

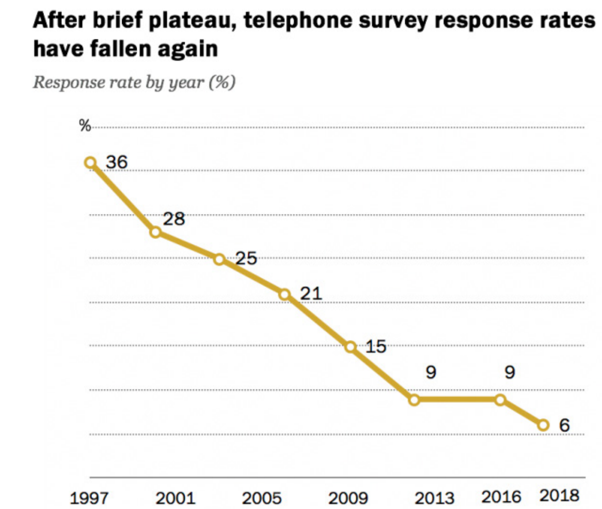


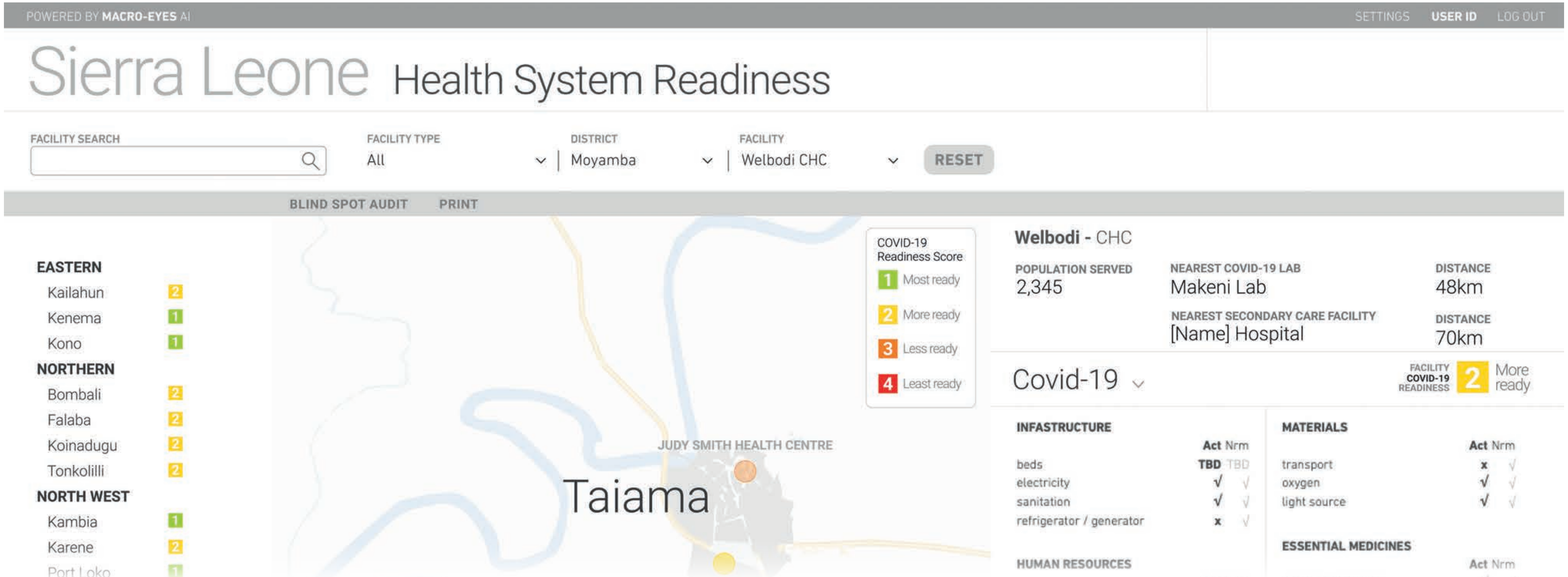
Fig. 14. Decline in response rates requires new data collection methods.

What's the Alternative?

The WHO developed a suite of tools — Capacity Assessment Modules — for COVID-19. The assessments use a series of phone interviews with stakeholders or in-person visits to extract information about the health facilities and the system writ large. The majority of the WHO modules target hospital case management of COVID-19. There are 58 hospitals in Sierra Leone: 4% of the total number of health facilities in the country. The WHO tools take the pulse of the health system but, for a number of reasons, focus mostly on one part or level. In the summer of 2020, the MOHS made a choice and conducted a health facility assessment (HFA) at ~130 primary care sites to get a better understanding of readiness to respond to COVID-19. In October, MOHS was able to roll out a rapid facility assessment (RFA) at select hospitals in Sierra Leone, but only a limited sample size was included. The HFA and RFA covered 30% of health facilities in Sierra Leone. Much like a wearable smart device, Striata allows the government to take the pulse of both primary and secondary health facilities and monitor them in near real time. When the COVID-19 pandemic hit Sierra Leone, MOHS had to rely on data already held and hope nothing had changed considerably, as was the case with almost every other country in the world.

In the ideal setting, the WHO Capacity Assessment Modules for COVID-19 would be deployed alongside the Macro-Eyes AI health facility classification tool, allowing more readily available insights to be shared with more nodes of data, to create a more comprehensive picture of health facility readiness.

Alternative Scenario	>	Outcome
Rely on out-of-date data	**and hope**	nothing's changed
BYOD [bring your own data] publish framework	**and hope**	countries will input data to self-assess or the data has been effectively audited
Assess in person (e.g., SARA) which takes 9-12 months; is organizationally intensive	**and hope**	resources trickle down; information trickles up.



What We Learned

It is possible to develop and train ML systems in a highly limited data environment. Supportive and collaborative in-country stakeholders (i.e., Sierra Leone MOHS, DSTI, Dimagi, Living Goods and GRID3) made this possible.

Macro-Eyes applied unsupervised learning (carefully constructing graph neural networks) to machine-learn groups of health facilities that share common characteristics. The phenotypes enhanced and validated the binning of the COVID-19 readiness scores into four categories from the "most" to the "least" COVID-19 ready.

Macro-Eyes used satellite imagery (high- and low-resolution) and a web scraper tool to enhance health facility classifications. Low-resolution satellite imagery contributed to understanding shocks to the health system, while high-resolution satellite imagery was used to predict the state of electrification for health facilities across Sierra Leone. The web scraper tool was used to help verify and understand contextual clues the satellite imagery provides.

Striata was built taking a health systems approach and the GoSL is considering use-cases beyond the COVID-19 effort, using this capability to assess each health facility in order to create impact across multiple areas.

Striata does not make health surveys obsolete, but supports Ministry leaders to target how and where resources are used. When targeted surveys are paired with ML, faster, far less expensive data can be collected from points on the map where there is high uncertainty. Most importantly, the results can then be scaled to provide greater clarity for similar sites and conditions across the map.

The Future

To be most effective, COVID-19 resources need to be allocated to places where they will have the most impact and save the most lives.

Health facility readiness is the foundation for a national strategy to provide the insight needed to efficiently match available resources to facilities and sub-populations.

The strain that COVID-19 places on health systems is not unique to Sierra Leone. The effective distribution of limited resources — while making best use of the health system as a whole — is a challenge faced by every nation.

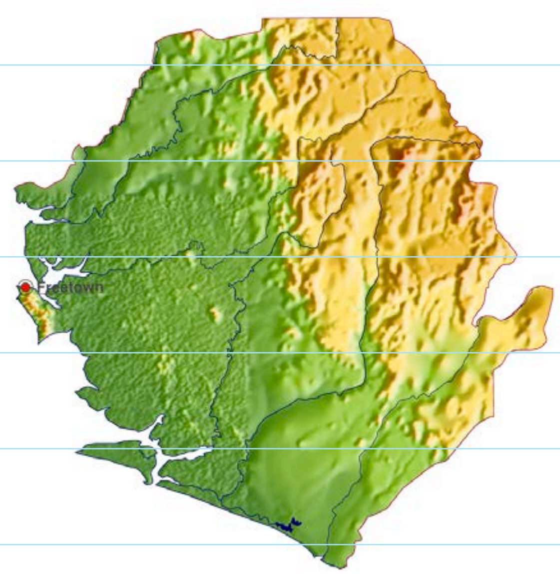
Striata helps decision-makers deploy resources strategically, so as to save the most lives.

"The Africa CDC has been trying to amass data on how many ventilators and intensive care units each country has, so it can model what needs will arise if there is an explosion of cases. ***But even collecting the data is not easily attainable and extremely expensive***," ~Benjamin Djoudalbaye, Africa Centers for Disease Control and Prevention, in *The New York Times.* [1]

1 "10 African Countries Have No Ventilators. That's Only Part of the Problem," The New York Times, April 18, 2020; [emphasis added].

Table 1: 18 variables shared across the Sierra Leone 2017 Service Availability and Readiness Assessment (SARA) Plus and the Sierra Leone MOHS COVID-19 survey from May 2020

Sl #	Variables
1	NUMBER OF **INPATIENT BEDS**
2	NUMBER OF **MATERNITY BEDS**
3	NUMBER OF CHO **CHO | COMMUNITY HEALTH OFFICERS**
4	ACCESS TO **CLEAR RUNNING WATER**
5	ACCESS TO **ENVIRONMENTAL DISINFECTANT**
6	ACCESS TO **HAND WASHING SOAP**
7	NUMBER OF STATE-ENROLLED COMMUNITY HEALTH NURSES **SECHN | COMMUNITY HEALTH NURSES**
8	NUMBER OF **LABORATORY TECHNICIANS**
9	NUMBER OF **CLEANER-PORTERS**
10	AVAILABILITY OF **ONSITE POWER SOURCE**
11	AVAILABILITY OF **REFRIGERATOR**
12	AVAILABILITY OF **OXYGEN**
13	AVAILABILITY OF **ALCOHOL RUB**
14	AVAILABILITY OF **IBUPROFEN**
15	AVAILABILITY OF **PARACETAMOL**
16	AVAILABILITY OF **LIDOCAINE**
17	AVAILABILITY OF **AMOXICILLIN**
18	AVAILABILITY OF **MAGNESIUM SULPHATE**



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