

## Using Machine Learning for Climate Related Impact Evaluations

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

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## Key Messages

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

## Introduction

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

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

In this article, Fraym examines the potential for applying artificial intelligence (AI) and machine learning (ML) to impact evaluations. We begin by exploring several AI/ML-based approaches that will become increasingly relevant for efficiently assessing African communities' vulnerability to climate change. Next, we outline a modified vulnerability index that builds upon past studies, which we then map down to the 1 km<sup>2</sup> level. Third, we apply this new approach to Malawi and Mali to highlight how this type of localized vulnerability mapping can provide actionable insights for program design and ongoing monitoring efforts. Lastly, we conclude with several takeaways and areas for further exploration.

## Using AI/ML for Impact Evaluations

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

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

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

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

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

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

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

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

## Methodology

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

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

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

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

**Table 1: Climate Vulnerability Index Methodology<sup>2</sup>**

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

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

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

### Case Studies and Analysis – Malawi and Mali

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

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

### Malawi

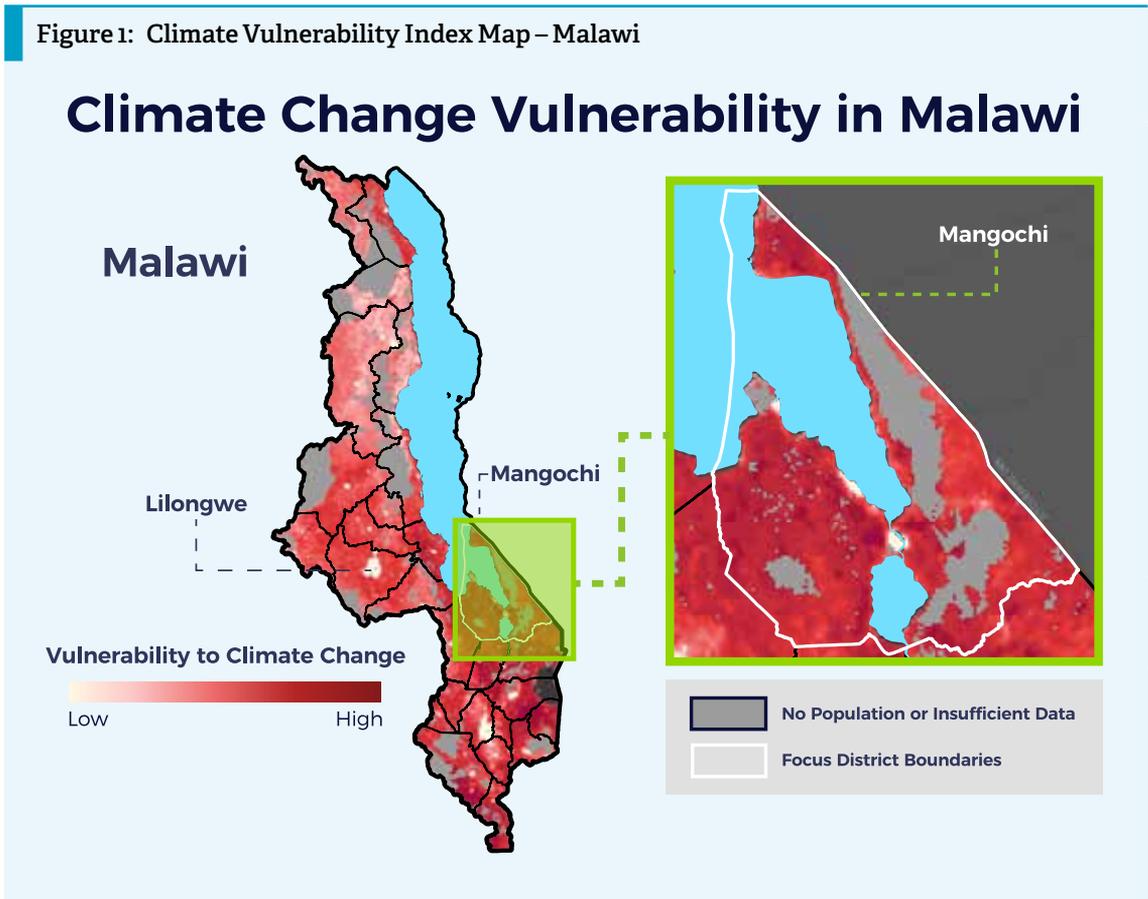
The vulnerability map of Malawi highlights the country’s southern region as most vulnerable. In 2017, 46 percent of households in southern communities experienced some form of drought, 10 percentage points higher than households in the central region, and 25 percentage points higher than the north. As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

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

### Profile

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

Figure 1: Climate Vulnerability Index Map – Malawi



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

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

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

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

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

## Mali

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

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

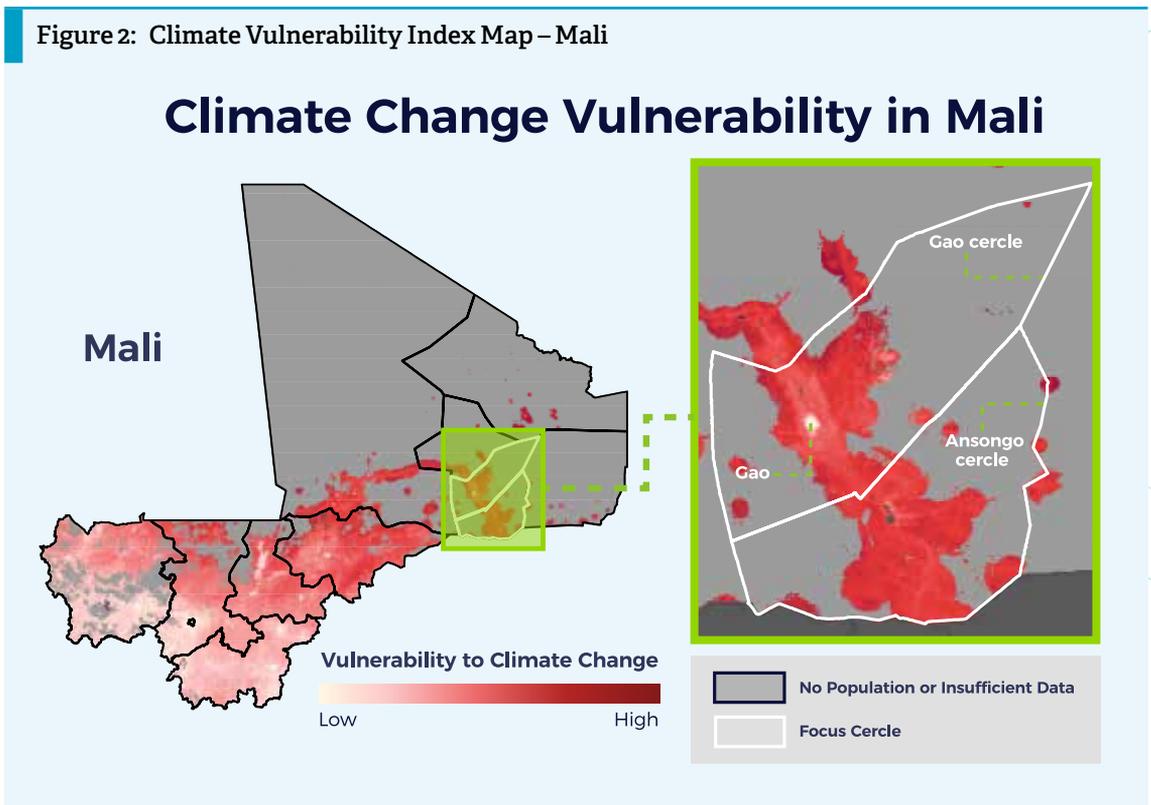
**Profile**

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

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

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

Figure 2: Climate Vulnerability Index Map – Mali



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

## Conclusion

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

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

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

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## Endnotes

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

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

## References

- Bishop, R., 2017. *Confronting climate change: Africa's leadership on an increasingly urgent issue*. Brookings Institute, Washington, DC.
- Brooks, N., Rai, N., Anderson, S., 2018. 'How integrated monitoring and evaluation systems can help countries address climate impacts,' *Briefing: iied*, August, pp. 1–5.
- Caffrey, P., Farmer, A. 2014. *Mali climate vulnerability mapping: African and Latin American resilience to climate change (ARCC)*. USAID, Washington, DC.
- Engstrom, R., Hersh, J., Newhouse, D., 2017. 'Poverty from Space; Using High-Resolution Satellite Imagery for Estimating Economic Well-Being,' World Bank, Poverty and Equity Global Practice Group, <http://documents.worldbank.org/curated/en/610771513691888412/pdf/WPS8284.pdf>
- Gbetibouo, G.A., Ringler, C., 2009. *Mapping South African farming sector vulnerability to climate change and variability: a subnational assessment*. International Food Policy Research Institute, Geneva.
- Government of Malawi (2018), National Resilience Strategy: Breaking the Cycle of Food Insecurity in Malawi, Government of Malawi. viewed 9 Feb 2020, [https://www.usaid.gov/sites/default/files/documents/1860/Malawi\\_National\\_Resilience\\_Strategy.pdf](https://www.usaid.gov/sites/default/files/documents/1860/Malawi_National_Resilience_Strategy.pdf).
- Hahn, M.B., Riederer, A.M., Foster, S.O., 2009. 'The Livelihood vulnerability index: A pragmatic approach to assessing risks from climate variability and change - A case study in Mozambique.' *Global Environmental Change*, vol. 19, 74–88.
- McKenzie, D., 2018. 'How can machine learning and artificial intelligence be used in development interventions and impact evaluations,' *Development Impact*, 5 March, viewed 8 Feb 2020, <https://blogs.worldbank.org/impactevaluations/how-can-machine-learning-and-artificial-intelligence-be-used-development-interventions-and-impact>.
- Moody, D., Brumby, S.P., Chartrand, R., Keisler, R., Mathis, M., Beneke, C.M., et al. 2017. 'Satellite imagery analysis for automated global food security forecasting,' *American Geophysical Union*, viewed 8 Feb 2020, <https://ui.adsabs.harvard.edu/abs/2017AGUFMGC33A1055M>.
- Parthasarathy, R., Rao, V., Palaniswamy, N., 2019. 'Deliberative Democracy in an Unequal World: A Text-As-Data Study of South India's Village Assemblies,' *American Political Science Review*, vol. 113, no. 3, pp. 623–640, viewed 8 Feb 2020, DOI 10.1017/S0003055419000182.
- Samii, C., Paler, L., Daly, S.Z., 2016. 'Retrospective causal inference with machine learning ensembles: an application to anti-recidivism policies in Colombia,' *Political Analysis*, vol. 24, pp. 434–456.
- USAID, 2019. *Fiscal Year 2019 Development Food Security Activities in Madagascar and Malawi*, Office of Food for Peace, viewed 9 Feb. 2020, [https://www.usaid.gov/sites/default/files/documents/1866/FINAL\\_FY\\_19\\_DFSA\\_RFA\\_for\\_Madagascar\\_and\\_Malawi.pdf](https://www.usaid.gov/sites/default/files/documents/1866/FINAL_FY_19_DFSA_RFA_for_Madagascar_and_Malawi.pdf).
- USAID, 2020a. *Country Specific Information: Malawi*, USAID Office of Food for Peace, viewed 9 Feb 2020, [https://www.usaid.gov/sites/default/files/documents/1866/CSI\\_for\\_Malawi.pdf](https://www.usaid.gov/sites/default/files/documents/1866/CSI_for_Malawi.pdf).
- USAID, 2020b. *Fiscal Year (FY) 2020 Development Food Security Activity in Mali*, Office of Food for Peace, viewed 4 Feb 2020, [https://www.usaid.gov/sites/default/files/documents/1866/FY20\\_DFSA\\_RFA\\_for\\_Mali-1-13-20.pdf](https://www.usaid.gov/sites/default/files/documents/1866/FY20_DFSA_RFA_for_Mali-1-13-20.pdf).

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