Research Brief

Introduction

Using agricultural and economic characteristics in African nations as test cases, new Stanford University research demonstrates the use of satellite data to address the long-standing problem of accurate data collection in developing countries. An often cited challenge in achieving development goals aimed at poverty and hunger reduction is the lack of reliable on-the-ground data. Limited or insufficient data makes it difficult to establish baseline conditions and to assess effectiveness of various aid programs. In the past, researchers and policymakers had to rely on ground surveys, which are expensive, time-consuming, and rarely conducted. This has led to large data gaps in mapping sustainable development goal progress, such as in agricultural and poverty statistics.

Of the 17 Sustainable Development Goals (SDGs) identified and approved by the United Nations in 2015, the two that top the list are goals to end poverty and eliminate hunger. While progress was made towards poverty alleviation under the Millennium Development Goals (MDGs), the forerunner to the SDGs, much work remains to be done. Efforts under the MDGs experienced regional differences in success rates, with many of the poorest countries delivering some of the lowest levels of progress. This brief is based on two studies that used satellite imagery—one to measure agricultural productivity and the other to map poverty—to help achieve broader development goals.





Photo credit: Marshall Burke

About the Stanford Center on Food Security and the Environment

The Center on Food Security and the Environment addresses critical global issues of hunger, poverty and environmental degradation by generating vital knowledge

and policy-relevant solutions. FSE is a joint effort of the Freeman Spogli Institute for International Studies and the Stanford Woods Institute for the Environment.

Data Science for Food Security

Assessing Corn Yields

The majority of farms in many African countries are small family farms, or smallholder farms, and are less than one acre in size. Smallholder crop yield data is lacking in both quality and quantity. Much of it is based on self-reported data, which often contain errors of 50 percent or more. Focusing on an area in western Kenya, researchers used satellite imagery to estimate crop yield and compared this data with ground surveys to see if the satellite data was accurate. Ground surveys can be slow and costly, meaning this method is less than ideal for larger-scale operations. The study tested a second approach that does not use the survey data, instead applying a computer model of crop growth and local weather conditions to data extracted from the satellite imagery. The results demonstrate potential for the satellite and computer model to predict accurate corn yield estimates without using the more expensive survey data. This method would lower both the cost and time commitment previously needed for predicting small farm productivity.

Policy Implications

Agricultural interventions by government organizations, NGOs, or other groups will be improved

Estimates of per capita consumption in four African countries. Stanford researchers used machine learning to extract information from high-resolution satellite imagery to identify impoverished regions in Africa.

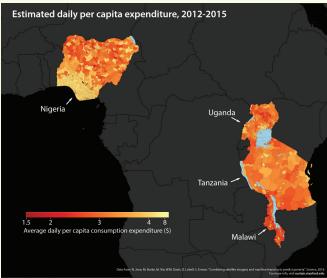


Photo credit: Neal Jean et al.

in the short- and long-term by filling in the data gaps in current crop yield measurements. Inexpensive crop yield data collected from satellite imagery will aid policymakers by enabling the following:

- Better targeting of agricultural interventions
- Better evaluation of intervention impact
- Long-term measurement of yield gaps, as well as their recurring causes
- Development of financial tools for farmers, such as insurance or credit products

Such improvements will increase the efficacy of government organizations, NGOs, and other groups, allowing them to progress towards their goals of eliminating hunger and ensuring food security.

Poverty Prediction

Similar to the method used in the crop yield study, the researchers used high-resolution satellite images to predict economic characteristics of five African countries. This information could help policymakers, development agencies, and aid organizations determine where to target relief efforts in impoverished zones.

Current methods for determining the economic status in defined geographic areas have weaknesses. For example, measurements taken of night-time luminescence cannot distinguish between poor, low-lit areas that are densely populated and wealthy, well-lit areas that are less populated. Instead, the researchers used machine learning to extract socioeconomic data from high-resolution daytime satellite imagery, checking the findings against recent local-level data. Without being told what to look for, the machine learning algorithm learned to pick out features such as roads, urban areas and farmland—that are predictive of economic well-being. The model was able to project average household consumption and asset wealth across multiple African countries, accurately predicting the economic status of different regions. The model can also be applied to other countries that are different economically and politically from the five sample nations.

Data Science for Food Security

Policy Implications

Accurate measurements of economic characteristics are essential to shaping government and international development organizations' decisions on where to send aid. These measurements inform global efforts to understand and track progress towards improving human livelihoods. Currently, a large data gap exists for economic measurements, which diminishes government and aid organizations' efficacy in providing relief. Data gaps are most severe in the following areas:

- Mapping economic characteristics
- · Identifying areas of greatest need
- Evaluating the outcome or the efficacy of relief efforts

This approach will help fill in those gaps. Furthermore, it can produce low-cost, granular data to predict the economic status of different regions. These measurements are of great interest to the international community, which needs this information to evaluate progress made on efforts such as the United Nations Sustainable Development Goals.

Conclusion

Advancements in satellite imagery technology have the potential to make a large, positive impact on the collection of data for food security. By applying machine learning and computer models to data collected from high-resolution satellite imagery, researchers and policymakers will have access to poverty statistics that previously would have taken too much time or money to collect. Researchers expect more advances in these types of studies in the near future as satellite images are being taken more frequently. Policymakers in government, NGOs and other international aid organizations will be able to

make more informed decisions on how to end poverty and improve food security in the world's developing nations. They will also be able to determine which aid strategies work best and adjust future relief plans accordingly. Data collection using satellite imagery has the potential to fill in the gaps in development data to work towards food security and other sustainable development goals.

About the Researchers

Marshall Burke is an Assistant Professor in the Department of Earth System Science and Center Fellow at the Center on Food Security and the Environment at Stanford University, and Research Fellow at the National Bureau of Economic Research. His research focuses on social and economic impacts of environmental change, and on the economics of rural development in Africa.

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This brief is based on findings from the papers "Satellitebased assessment of yield variation and its determinants in smallholder African systems" http://www.pnas.org/ content/114/9/2189.full published in Proceedings of the National Academy of Sciences in 2017 and "Combining satellite imagery and machine learning to predict poverty" http://science.sciencemag.org/content/353/6301/790 published in Science in 2016.



Freeman Spogli Institute for International

FSE is a joint initiative of the Stanford Woods Institute for the Environment and the Freeman Spogli Institute for International Studies at Stanford University.

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