

# Applications and Considerations for AI-EO for Agriculture in Sub-Saharan Africa

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## ABSTRACT

With the ever-growing urgency of food insecurity and the threat of climate change, there is increasing interest in using artificial intelligence for Earth observations (AI-EO) for agriculture, particularly in Sub-Saharan Africa (SSA). This paper provides an overview of the primary research areas within AI-EO for agriculture in SSA. We discuss examples and limitations of current research as well as opportunities for future work. In addition, we identify ten key considerations for future efforts involving AI-EO for agriculture in SSA.

**Keywords:** Artificial intelligence for Earth observations (AI-EO), Food Insecurity, Agriculture

## 1 Introduction

Adapting to and mitigating climate change while addressing food insecurity in Sub-Saharan Africa (SSA) requires technologies to improve rural livelihoods with minimal environmental costs (Sasson 2012; Burney, Davis, and Lobell 2010). These technological solutions must also be accessible to rural communities. Artificial intelligence (AI) offers great promise for developing solutions that improve food security outcomes for people in SSA in a climate-smart way, but not all AI solutions are accessible or practical for farmers in SSA today. Most people think of precision agriculture as the primary use case for AI in agriculture, including self-driving tractors, automation of farm equipment, and scheduling of inputs like fertilizer or irrigation (Rolnick *et al.* 2019). While these are important and useful applications, most precision agriculture applications are out of reach for the majority of farmers in SSA who do not have access to the required infrastructure in the near term.

There is, however, large potential in the near term for AI solutions that use Earth observation (EO) data which enable agricultural analyses and insights at global scales (Becker-Reshef *et al.* 2018). Many of these datasets are also freely available, making EO-based solutions affordable and globally scalable (Nakalembe *et al.* 2021a). AI approaches that use EO data, which we call AI-EO, can support policy structures that accelerate the design and adoption of climate-smart agriculture (CSA) and impact farmer livelihoods by increasing access to actionable early warning, risk financing or insurance, and better access to farm inputs and markets (Onyango *et al.* 2021). AI-EO technologies can help improve and scale measurements of interventions and reduce the cost of farm management decisions that maximize inputs (e.g., water and energy). They can also enable measurement of agricultural greenhouse gas emissions and direct investments in opportunities for greenhouse gas (GHG) mitigation such as yield improvements and cover cropping (Burney, Davis, and Lobell 2010; Rolnick *et al.* 2019).

However, AI-EO solutions for agriculture in SSA are still limited. For example, many models are not generalizable across heterogeneous landscapes. There are relatively few studies that develop or evaluate methods for SSA, labeled datasets for training and evaluating models in SSA, and solutions that are feasible in resource-constrained contexts. In this paper, we describe the principal sub-fields of research in AI-EO



for agriculture in SSA and discuss examples and limitations of existing work in each application. We also distill our experience working on AI-EO for agriculture in Africa into ten considerations that we posit are important for the research community to consider in future work on AI-EO for agriculture in SSA.

We hope that this paper will serve as both a summary of the state of the field and a guide for researchers who want to pursue research in applications of AI-EO for agriculture in SSA.

## **2 Key AI-EO Applications**

This section describes the main sub-problems within AI-EO applications for agriculture in SSA. The outputs from solutions in these sub-problems are critical components for downstream applications and products that inform SSA policies, programs, and decision-making for food security and climate-smart agriculture. Products such as crop type maps and yield estimates are necessary for computing agricultural statistics (e.g., crop production at the national or regional scale) to forecast surpluses or deficits of food production to inform trade and aid decisions (Lobell 2013; Nakalembe *et al.* 2021a; Becker-Reshef *et al.* 2018, 2019). Other downstream uses include insurance and risk financing (World Bank Group 2019; Skakun *et al.* 2016), assessing impacts of events like conflict or natural disasters on food security (Olsen *et al.* 2021; Li *et al.* 2022), and measuring progress towards Sustainable Development Goals.

(Whitcraft *et al.* 2019), among others. For each application, we reference current solutions and discuss limitations of existing work that would be impactful to address in future work. We focus our discussion on work that explicitly addresses applications in small-holder dominated SSA; therefore, prior work in these applications for regions outside of SSA may not be included.

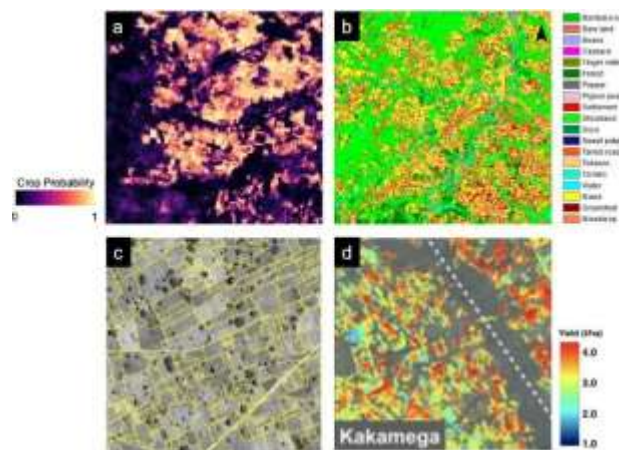
### **2.1 Cropland Mapping**

Cropland maps are derived from EO data inputs and indicate where crops are growing spatially. Cropland maps are a critical component for agricultural monitoring with satellite data. In EO-based yield modeling and forecasting systems, cropland maps are required to exclude pixels in satellite images that represent other land cover classes and segments where cropland is sparse or non-existent (Franch *et al.* 2021, 2015; Nakalembe *et al.* 2021b; Zhang *et al.* 2019). Cropland mapping involves binary classification of spatial units in a region (e.g., pixels with a specific spatial resolution) as containing cropland or not. The spatial resolution of the crop map depends on the resolution of the satellite data inputs used (e.g., 10 m/pixel if using the Sentinel-2 dataset (Kerner *et al.* 2020), 100 m/pixel if using the PROBA-V satellite (Buchhorn *et al.* 2020), or 30 m/pixel if using the Landsat dataset (Potapov *et al.* 2021)). Figure 1a shows an example model output for cropland classification from Kerner *et al.* (2020). Cropland maps are also frequently referred to as crop “masks” because they are used to mask out pixels in satellite images (or samples in other spatial datasets) that do not contain crops so that subsequent analysis includes only the inputs representing cropland (Nakalembe *et al.* 2021b; Zhang *et al.* 2019). Cropland maps can also be derived from land cover maps which provide a multi-class classification of spatial units into land cover (e.g., water, forest, cropland). Crop masks are derived from land cover maps by aggregating the non-cropland classes into a single non-crop class (Cihlar 2000).

Today, most models used for cropland or land cover classification are machine learning models. Tree-based classifiers such as decisions trees and random forests are most commonly used (e.g., Jin *et al.* (2018); Potapov *et al.* (2021); Xiong *et al.* (2017); Buchhorn *et al.* (2020)). Deep learning approaches have been gaining popularity in recent years (Kerner *et al.* 2020; Ienco *et al.* 2019; Li *et al.* 2016). While the accuracy of public cropland maps is generally high in developed regions, prior studies have shown significantly lower accuracy in SSA. For example, the errors reported for crop area estimates in Potapov *et al.* (2021) were the lowest in Africa, and Leroux *et al.* (2014) found that user accuracy (also known as precision) was as low as

17% in eastern Africa.

This is partly because farms in SSA are predominantly smallholder or subsistence farms which are typically 5 hectares (Samberg *et al.* 2016), which can be difficult to detect accurately without very high resolution satellite datasets (which are not freely available). Another limiting factor is the lack of publicly available labeled datasets for agriculture in SSA compared to other regions. Many widely-used cropland maps are derived from global or regional land cover maps such as the MODIS Land Cover Product (Friedl *et al.* 2010) or ESA CCI Land Cover Map (Zanaga *et al.* 2021), which tend to have poor accuracy for SSA due to insufficient resolution, lack of labeled data for training and evaluation, and/or lower priority for optimizing performance for SSA compared to other regions based on project objectives (Leroux *et al.* 2014; Lesiv *et al.* 2017).



**Figure 1:** Example outputs from AI-EO models for a) cropland classification in Togo (Kerner *et al.* (2020)), b) crop type classification in Malawi (Kpienbaareh *et al.* (2021)), c) field boundary delineation in Nigeria (Persello *et al.* (2019)), and d) yield estimation in Kenya (Jin *et al.* (2019)).

## 2.2 Crop Type Mapping

Crop type mapping is similar to cropland mapping, except the goal is to classify specific crop types (e.g., maize) in each spatial unit (Zhang *et al.* 2019). Crop type mapping is usually framed as a multi-class classification problem but can be framed as binary classification where the positive class is the crop type of interest, and the negative class includes all other crop types and land cover classes (i.e., one vs. rest). Like cropland maps, crop type maps identify where certain crops are grown and restrict the satellite data inputs in downstream analyses like yield estimation to locations where certain crops are grown. Crop type maps should be updated every season because farmers may change crops grown in a particular field (Nakalembe *et al.* 2021b). Before crop type mapping, cropland masks are frequently applied to satellite datasets to restrict crop type classification to only those pixels likely to be cropland. Like cropland mapping, tree-based classifiers like decision trees and random forests are frequently used for crop type mapping (e.g., Song *et al.* (2017); Wang *et al.* (2020); Forkuor *et al.* (2014); Kpienbaareh *et al.* (2021); Azzari *et al.* (2021)). Deep learning approaches, especially recurrent neural networks that learn important patterns in time for discriminating between crop-specific growth patterns during the growing season, have gained popularity in recent years (e.g., Tseng *et al.* (2021a); Rustowicz *et al.* (2019); Kussul *et al.* (2017)). Figure 1b shows an example model output for crop type



**Figure 2:** Comparison of images containing crop fields in southern Uganda acquired by three remote sensing platforms with different spatial resolutions.

From left to right in figure 2: drone image (4 cm/pixel, taken by author CLA in 2016), CNES/Airbus base map in Google Earth (0.5 m/pixel, from 2021 base map), and Sentinel 2 image (10 m/pixel, acquired 2021). Banana and maize crops can be identified in the drone image but not the CNES/Airbus or Sentinel-2 satellite images. Other crops known to be present from ground-truth observation, such as beans and sweet potatoes, cannot be identified from satellite images.

### Classification in Malawi from Kpienbaareh *et al.* (2021)

Lack of publicly-available labeled datasets is the biggest challenge for advancing research on crop type mapping methods in Africa (as well as globally). While some recent work has proposed promising approaches for improving crop type classification results with limited labeled data using transfer learning and few-shot learning methods like meta-learning (Tseng *et al.* 2021a), most prior work relies on large labeled datasets that are not currently available for SSA. Furthermore, even if a model can be trained efficiently using a small number of labeled samples, robust evaluation of the resulting crop type map (which involves dense inference over an entire region) still requires many labels. While land cover labels (including cropland) can usually be annotated using photo-interpretation of high-resolution satellite images (e.g., as in Kerner *et al.* (2020)), crop type cannot be determined by inspecting very high-resolution satellite images in most cases (e.g., Figure 2). Crop type labels are typically obtained by physically visiting fields and recording the crop being grown at a specific location (latitude and longitude) and date; thus, these labels are often called ground-truth labels. This process is slow, expensive, and physically taxing. Inter-cropping and mixed-cropping is common practice in SSA that presents an additional challenge for AI-EO methods. While it is possible to physically identify multiple crops growing in the field from in-situ observation, it is more difficult to disaggregate the signals when multiple crops are grown at the same pixel location. Thus, current methods typically treat intercropped fields as a single aggregate class or use only the label for the crop assumed to be the dominant crop in the field.

### 2.3 Field Boundary Delineation

The goal of field boundary delineation is to predict the polygonal boundaries of fields to identify individual instances of fields. Field boundary delineation is of interest to stakeholders such as government statistics agencies for guiding sampling and area estimation methods. Field boundaries are also used in sampling frames that provide statistically sound estimates of cropped area and are helpful for sub-field assessments of inputs, crop performance, and production (Masoud, Persello, and Tolpekin 2019; Bush and House;

Davies 2009). This task is analogous to instance segmentation in computer vision using methods like Mask R-CNN (Meyer, Lemarchand, and Sidiropoulos 2020), though most recent work on field boundary delineation has used semantic segmentation methods like U-Nets followed by post-processing steps to isolate individual field instances (Wang, Waldner, and Lobell 2022; Aung *et al.* 2020; Waldner and Diakogiannis 2020; Persello *et al.* 2019; Masoud, Persello, and Tolpekin 2019). Figure 1c shows an example model output for field boundary delineation in Nigeria from Persello *et al.* (2019).

A major roadblock for field boundary delineation in SSA is insufficient spatial resolution of publicly available satellite datasets. Smallholder fields in SSA are often smaller than 1 ha (100m X 100m), while the resolution of Sentinel-2—the highest resolution freely-available satellite dataset with global coverage today—is 10m X 10m. Accurately identifying the boundaries of these small-scale fields requires very high-resolution satellite datasets that are currently only available from commercial providers (Wang, Waldner, and Lobell 2022; Estes *et al.* 2021; Persello *et al.* 2019). As in the case of other applications discussed in this section, there are very few public datasets that provide field boundary labels in SSA (e.g., Kehs *et al.* (2021)). Prior work has addressed this limitation using active learning (Estes *et al.* 2021) and by combining transfer learning and weak supervision (Wang, Waldner, and Lobell 2022). These labels are often challenging to annotate without ground-truth or farmer inputs. In some cases, the apparent boundary of a field in a high-resolution image is different from what a farmer on the ground considers to be the boundary. These “true” boundaries may only be discernible when inspecting images from many times during the growing season or checking informal markers signifying field boundaries on the ground. Thus, many field boundary delineation approaches focus on identifying field boundaries as they are understood by human annotators of images rather than ground-truth field boundaries (Wang, Waldner, and Lobell 2022; Estes *et al.* 2021).

## 2.4 Yield Estimation

Yield estimation is a regression task in which models estimate the crop harvested per unit area (e.g., kg or tonnes per hectare). Crop yields can be estimated at the field scale or regional to national scales, but most current work is at the regional or national scale. AI-EO methods for yield estimation may also be evaluated by how early the end-of-season yield can be accurately forecast in the growing season. For example, Franch *et al.* (2021) estimated end-of-season yield as early as 2 to 2.5 months before harvest. Models for estimating yield that can support strategies for increasing yields are essential for CSA in SSA, where increases in crop production over recent decades have largely been driven by increases in the cultivated area rather than yields (Sahajpal *et al.* 2020). Most ML approaches for yield estimation use decision tree-based methods such as random forests (Sahajpal, Becker-Reshef, and Coutu 2020) and XGBoost (Ajadi *et al.* 2021), but recent work has presented a wide variety of deep learning-based solutions to yield estimation including Deep Gaussian Processes (You *et al.* 2017), graph neural networks (Fan *et al.* 2021), and recurrent neural networks (Wang *et al.* 2018; Hosseini *et al.* 2021). Other approaches leverage crop simulation and statistical regression models to estimate yield (Lobell *et al.* 2015; Azzari, Jain, and Lobell 2017; Sadeh *et al.* 2021; Franch *et al.* 2021; Davenport *et al.* 2019). However, few studies have focused on yield estimation for SSA compared to more data-rich regions like the US or Europe (Jin *et al.* 2019; Azzari, Jain, and Lobell 2017; Lobell *et al.* 2018). Figure 1 shows an example model output for yield estimation in Kenya from Jin *et al.* (2019).

## 2.5 Pest, Disease, and Anomaly Detection

AI-EO can be useful for detecting and tracking pest and disease impacts over large areas during the growing season to minimize pest and disease damage to crops (Abd El-Ghany, Abd El-Aziz, and Marei 2020). There has been some research on pest/disease detection in EO data, for example, in detecting rice sheath blight (Qin and Zhang 2005; Qin *et al.* 2003), wheat streak mosaic (Mirik *et al.* 2013), and whiteflies in cassava

(Yang and Everitt 2011). Most of these studies use very high-resolution satellite imagery that is not publicly or globally available and do not leverage modern AI techniques. Recent work leveraging AI techniques to improve surveillance, monitoring and early warning for disease threats mostly focus on in-situ diagnosis of plant disease using cell phone images (Mrisho *et al.* 2020; Tsubira *et al.* 2020; Rubanga *et al.* 2020; Sanga *et al.* 2020) or ground-based robots (Liu *et al.* 2021).

AI approaches that use globally-available EO datasets combined with in-situ datasets could monitor the incidence and impact of pests and diseases over larger areas. These approaches could also detect other in-field anomalies such as nutrient deficiencies or weeds. While there is potential for high-impact AI-EO solutions to detect pests, diseases, and other anomalies over large areas, there have been few studies in this area (Gold 2021). This is partly due to the lack of publicly-available high-resolution satellite datasets and ground-truth labels needed to train and evaluate AI models.

## 2.6 Other Use Cases

While the previous section described the main sub-fields in AI-EO for agriculture in SSA, there are many other emerging use cases that we do not describe in detail in this paper. Examples include but are not limited to livestock/rangelands monitoring (Allred *et al.* 2021), groundwater estimation (Manziona and Matulovic 2021; Aryafar *et al.* 2019), soil organic carbon stocks monitoring (Rostaminia *et al.* 2021), and risk assessments that combine AI-EO model outputs with other datasets such as soil, food price, and socioeconomic data.

## 3 Considerations

This section distills our experience working on AI-EO methods for agriculture in SSA into ten points that we believe are important to consider in ongoing and future work in this field. These considerations are a combination of recommendations for future work and lessons learned from prior work that we posit can increase the impact of AI-EO research methods on agriculture in SSA.

- i. **Interdisciplinary teams are a requirement:** Developing robust, practical, and contextually relevant AI-EO methods for agriculture in SSA requires interdisciplinary teams including experts in AI, agriculture/agronomy, remote sensing, climate science, soil science, and local and regional practices. It is imperative to work across fields to develop innovative and applicable AI-EO solutions and systems that maximize benefits to end-users in SSA.
- ii. **Consider the resource context of stakeholders:** The resource context (e.g., cost, energy, or internet bandwidth) for the intended stakeholders or end-users must be considered at all stages of the research process, including algorithm selection/design and dissemination of model results. For example, internet costs may be prohibitive for certain AI systems (e.g., 1 GB of data costs 4.3% of monthly net income in Africa) (World Bank 2021). These constraints are rarely considered in AI research. Rather, there is a widespread belief that AI innovations will eventually become available to individuals in resource-poor settings rather than welcoming these requirements as drivers for AI innovation (De-Arteaga *et al.* 2018).
- iii. **Prioritize methods for limited labeled data:** Prioritizing research on AI-EO methods that optimize performance with limited labeled data is necessary for addressing the labeled data bottleneck for agriculture in SSA. This also benefits other application areas (e.g., species distribution modeling (Beery *et al.* 2021) or under-sampled languages in natural language processing problems (Adelani *et al.* 2021; Nabende *et al.* 2021)) and foundational AI advances (e.g., few shot learning). In addition to prioritizing algorithmic innovations for addressing limited labeled data, the community should prioritize more community-wide efforts to create publicly available labeled datasets for agriculture in SSA, such as the Lacuna Fund (Lacuna Fund 2020), Radiant Earth ML-Hub (Alemohammad 2021), and the Crop

Harvest dataset (Tseng *et al.* 2021b).

- iv. **Methods should be transparent and reproducible:** Many AI-EO studies and derived products are published without sufficient details (such as source code) for reproducibility or complete understanding of results. There is a need for greater transparency and accountability in AI-EO, including proper documentation and open methods that enable researchers across fields to trace and replicate prior work and compare methods to track progress in the field directly (Maskey *et al.* 2020).
- v. **Work with stakeholders from the beginning:** Stakeholders and end-users for agriculture applications in SSA should be consulted early in the research and development process to ensure researchers are working on problems that solve real end-user needs and that end-user resource constraints are considered. In addition, stakeholders can help inform the choice of metrics for evaluating AI-EO methods that are representative for real-world performance rather than defaulting to commonly used metrics in AI (Kerner 2020).
- vi. **Decolonize research methods and practices.** While most discussions of equity and ethics in AI and EO have traditionally focused on diversity and inclusion of under-represented groups, recent discussions for geoscience, in particular, have highlighted the legacy of colonialism and how researchers can consider decolonizing current practices in research. For example, Liboiron (2021) described how colonialism today can manifest in different ways than we traditionally envision in the context of colonialism—For instance, foreign researchers collecting data or samples on indigenous land without consent from residents (e.g., smallholder farmers in SSA). Researchers need to recognize the harms that have been done by colonialism and strive to conduct research in a way that does not perpetuate harm or reinforce negative power structures.
- vii. **Form meaningful partnerships with local institutions.** The majority of AI research today is being conducted in the US, Europe, and China (Savage 2020), making international partnerships between institutions in these regions and SSA a critical component for the success of agriculture applications in SSA. International partnerships could work toward creating an enabling environment for AI in SSA that provides resources for capacity building, recruiting talent, infrastructure for data and compute, and inclusive innovations. Partnering with local institutions to collect new and existing labeled datasets for AI-EO is a clear opportunity for collaboration. However, international partnerships should go beyond data collection to ensure the benefits of AI-EO innovations are realized for local end-users and can be sustained and extended by local researchers. Sustainability requires the necessary skills and infrastructure to be available locally. It is vital to recognize that institutional structures, human resources, and funding constraints might inhibit the uptake of AI-EO methods despite the enthusiasm of stakeholders to adopt solutions.
- viii. **Institutionalized investments are needed for sustainable solutions.** For investments like those resulting from international partnerships discussed in the previous point to be sustainable over the long term, there is a need for investments in data collection and research to be institutionalized by enduring organizations focused on the public good such as universities or government programs. It is crucial for core government agencies such as ministries of agriculture, statistics, and disaster management to build, invest in, and embrace AI-EO solutions. This requires supporting not only human resources but also the infrastructure for data collection, analysis, scientific research and collaboration, and communication to broad stakeholders. The cost of investments like data collection and compute infrastructure could be shared so that individual institutions' costs are minimized, for example, through innovation grants from governments or the African Union. (Nakalembe 2020).
- ix. **High-resolution imagery needs to be accessible for SSA.** Limited access to high-resolution satellite datasets is a significant roadblock for advancing research and adopting AI-EO applications for

smallholder agriculture in SSA. There is a need for community or cross-institution efforts to purchase data from commercial providers like Planet or Maxar for agriculture-related research in SSA. For example, the Norway International Climate and Forests Initiative (NICFI) Satellite Data Program made high-resolution Planet base maps freely available for projects related to forests in the world's tropics (Planet, Inc. 2021). A similar initiative could be implemented for agriculture.

- x. **Limitations of AI-EO solutions should be assessed and communicated.** While there is vast potential and excitement for AI-EO technologies for agriculture in SSA, researchers need to assess and communicate the limitations of new and existing solutions to potential stakeholders and end-users. While published research shows what benefits are possible, practical demonstrations that realize the promise of these solutions for stakeholders are still limited. Over-promising and under-delivering on the capabilities of AI risks disillusionment and loss of interest for stakeholders and funders of AI-EO solutions in agriculture in SSA. Furthermore, it is critical to perform rigorous evaluations to thoroughly assess and communicate the strengths and limitations of AI-EO models (indeed, any models) used to inform decisions or policies that affect people's livelihoods and outcomes (O'Neil 2016).

## 4 Conclusion

This paper described the principal sub-fields of research in AI-EO for agriculture in SSA. We discussed the limitations of existing methods and opportunities for future work in each application. We presented ten critical points that we believe are essential for the research community to consider in future work on AI-EO for agriculture in SSA based on our experiences. This paper serves as a brief summary of the state of AI-EO research and applications and a guide for researchers working on agriculture in SSA now and in the future.

**Opportunities for future work** Across the AI-EO applications for agriculture in SSA, there are common research topics for future research that would have substantial impact. To address the lack of labeled data across applications in SSA, research could focus on learning efficiently from limited labeled data as well as sparse, partial, and/or noisy labels. At the same time, more efficient and scalable approaches to data collection are needed to create datasets and benchmarks that represent real-world conditions and progress for agriculture in SSA. Future work could develop approaches for dealing with intercropping in classification and yield prediction models, as this is a common practice in SSA. Techniques for multi-fidelity data fusion are also required to combine satellite data sources with variable temporal and spatial resolution, quality, and other characteristics. Finally, there is a need for more equitable programs like the Lacuna Fund that fund researchers and organizations based in SSA to develop the datasets, models, and other capacity required to advance AI-EO capacity for agriculture in SSA.

## 5 Declarations

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## References

- Abd El-Ghany, N. M.; Abd El-Aziz, S. E.; and Marei, S. S. 2020. A review: application of remote sensing as a promising strategy for insect pests and diseases management. *Environ. Sci. Pollut. Res.*, 27(27): 33503–33515.
- Adelani, D. I.; Abbott, J.; Neubig, G.; D'souza, D.; Kreutzer, J.; Lignos, C.; Palen-Michel, C.; Buzaaba, H.; Rijhwani, S.; Ruder, S.; Mayhew, S.; Azime, I. A.; Muhammad, S. H.; Emezue, C. C.; Nakatumba-Nabende, J.; Ogayo, P.; Anuoluwapo, A.; Gitau, C.; Mbaye, D.; Alabi, J.; Yimam, S. M.; Gwadabe, T. R.; Ezeani, I.; Niyongabo, R. A.; Mukiiibi, J.; Otiende, V.; Orife, I.; David, D.; Ngom, S.; Adewumi, T.; Rayson, P.; Adeyemi, M.; Muriuki, G.; Anebi, E.; Chukwunke, C.; Odu, N.; Wairagala, E. P.; Oyerinde, S.; Siro, C.; Bateesa, T. S.; Oloyede, T.; Wambui, Y.; Akinode, V.; Nabagereka, D.; Katusiime, M.; Awokoya, A.; Mboup, M.; Gebreyohannes, D.; Tilaye, H.; Nwaike, K.; Wolde, D.; Faye, A.; Sibanda, B.; Ahia, O.; Dossou, B. F.; Ogueji, K.; Diop, T. I.; Diallo, A.; Akinfaderin, A.; Marengereke, T.; and Osei, S. 2021. Masakhaner: Named entity recognition for african languages. *Trans. Assoc. Comput. Linguist.*, 9: 1116–1131.
- Ajadi, O. A.; Barr, J.; Liang, S.-Z.; Ferreira, R.; Kumpatla, S. P.; Patel, R.; and Swatantran, A. 2021. Large-scale crop type and crop area mapping across Brazil using synthetic aperture radar and optical imagery. *International Journal of Applied Earth Observation and Geoinformation*, 97: 102294.
- Alemohammad, H. 2021. The case for open-access ML-ready geospatial training data. In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 1146–1148. IEEE.
- Allred, B. W.; Bestelmeyer, B. T.; Boyd, C. S.; Brown, C.; Davies, K. W.; Duniway, M. C.; Ellsworth, L. M.; Erickson, T. A.; Fuhlendorf, S. D.; Griffiths, T. V.; Jansen, V.; Jones, M. O.; Karl, J.; Knight, A.; Maestas, J. D.; Maynard, J. J.; McCord, S. E.; Naugle, D. E.; Starns, H. D.; Twidwell, D.; and Uden, D. R. 2021. Improving Landsat predictions of rangeland fractional cover with multitask learning and uncertainty. *Methods Ecol. Evol.*, 12(5): 841–849.
- Aryafar, A.; Khosravi, V.; Zarepourfard, H.; and Rooki, R. 2019. Evolving genetic programming and other AI-based models for estimating groundwater quality parameters of the Khezri plain, Eastern Iran. *Environ. Earth Sci.*, 78(3): 69.
- Aung, H. L.; UzKent, B.; Burke, M.; Lobell, D.; and Ermon, S. 2020. Farm Parcel Delineation Using Spatio-temporal Convolutional Networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 76–77.
- Azzari, G.; Jain, M.; and Lobell, D. B. 2017. Towards fine resolution global maps of crop yields: Testing multiple methods and satellites in three countries. *Remote Sensing of Environment*, 202: 129–141.
- Azzari, G.; Jain, S.; Jeffries, G.; Kilic, T.; and Murray, S. 2021. Understanding the Requirements for Surveys to Support Satellite-Based Crop Type Mapping.
- Becker-Reshef, I.; Barker, B.; Humber, M.; Puricelli, E.; Sanchez, A.; Sahajpal, R.; McGaughey, K.; Justice, C.; Baruth, B.; Wu, B.; *et al.* 2019. The GEOGLAM crop monitor for AMIS: Assessing crop conditions in the context of global markets. *Global Food Security*, 23: 173–181.
- Becker-Reshef, I.; Justice, C.; Whitcraft, A. K.; and Jarvis, I. 2018. Geoglam: a geo initiative on global agricultural monitoring. In *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium*, 8155–8157. IEEE.
- Beery, S.; Cole, E.; Parker, J.; Perona, P.; and Winner, K. 2021. Species Distribution Modeling for Machine Learning Practitioners: A Review. In *ACM SIGCAS Conference on Computing and Sustainable Societies*.
- Buchhorn, M.; Smets, B.; Bertels, L.; Roo, B. D.; Lesiv, M.; Tsendbazar, N.-E.; Herold, M.; and Fritz, S. 2020. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2018: Globe.
- Burney, J. A.; Davis, S. J.; and Lobell, D. B. 2010. Greenhouse gas mitigation by agricultural intensification. *Proc. Natl. Acad. Sci. U. S. A.*, 107(26): 12052–12057.
- Bush, J.; and House, C. 2000. The Area Frame: A Sampling Base For Establishment Surveys. Technical report, National Agricultural Statistical Service, Fairfax, Virginia.
- Cihlar, J. 2000. Land cover mapping of large areas from satellites: Status and research priorities. *Int. J. Remote Sens.*, 21(6-7): 1093–1114.
- Davenport, F. M.; Harrison, L.; Shukla, S.; Husak, G.; Funk, C.; and McNally, A. 2019. Using out-of-sample yield forecast experiments to evaluate which earth observation products best indicate end of season maize yields. *Environ. Res. Lett.*, 14(12): 124095.
- Davies, C. 2009. Area Frame Design for Agricultural Surveys. Technical report. De-Arteaga, M.; Herlands, W.; Neill, D. B.; and Dubrawski, A. 2018. Machine learning for the developing world. *ACM Transactions on Management Information Systems (TMIS)*, 9(2): 1–14.
- Estes, L. D.; Ye, S.; Song, L.; Luo, B.; Eastman, J. R.; zhi Meng, Z.; Zhang, Q.; McRitchie, D.; Debats, S. R.; Muhandu, J.; Amukoa, A. H.; Kaloo, B. W.; Makuru, J.; Mbatia, B. K.; Muasa, I. M.; Mucha, J.; Mugami, A. M.; Mugami, J. M.; Muinde, F. W.; Mwawaza, F. M.; Ochieng, J.; Oduol, C. J.; Oduor, P.; Wanjiku, T.; Wanyoike, J. G.; Avery, R.; and Caylor, K. K. 2021. High resolution, annual maps of the characteristics of smallholder-dominated croplands at national scales.
- Fan, J.; Bai, J.; Li, Z.; Ortiz-Bobea, A.; and Gomes, C. P. 2021. A GNN-RNN Approach for Harnessing Geospatial and Temporal Information: Application to Crop Yield Prediction. *arXiv preprint arXiv:2111.08900*.
- Forkuor, G.; Conrad, C.; Thiel, M.; Ullmann, T.; and Zoungrana, E. 2014. Integration of Optical and Synthetic Aperture Radar Imagery for Improving Crop Mapping in Northwestern Benin, West Africa. *Remote Sensing*, 6(7): 6472–6499.
- Franch, B.; Vermote, E.; Skakun, S.; Santamaria-Artigas, A.; Kalecinski, N.; Roger, J.-C.; Becker-Reshef, I.; Barker, B.; Justice, C.; and Sobrino, J. 2021. The ARYA crop yield forecasting algorithm: Application to the main wheat exporting countries. *International Journal of Applied Earth Observation and Geoinformation*, 104: 102552.
- Franch, B.; Vermote, E. F.; Becker-Reshef, I.; Claverie, M.; Huang, J.; Zhang, J.; Justice, C.; and Sobrino, J. A. 2015. Improving the timeliness of winter wheat production forecast in the United States of America, Ukraine and China using MODIS data and NCAR Growing Degree Day information. *Remote Sens. Environ.*, 161: 131–148.

- Friedl, M. A.; Sulla-Menashe, D.; Tan, B.; Schneider, A.; Ramankutty, N.; Sibley, A.; and Huang, X. 2010. MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sensing of Environment*, 114(1): 168–182.
- Gold, K. M. 2021. Plant Disease Sensing: Studying Plant-Pathogen Interactions at Scale. *Msystems*, 6(6): e01228–21.
- Hosseini, M.; Becker-Reshef, I.; Sahajpal, R.; Fontana, L.; Lafluf, P.; Leale, G.; Puricelli, E.; Skakun, S.; and Varela, M. 2021. Crop Yield Forecast at Field Scale Using Deep Neural Network Algorithm. In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 6080–6083. IEEE.
- Ienco, D.; Interdonato, R.; Gaetano, R.; and Minh, D. H. T. 2019. Combining Sentinel-1 and Sentinel-2 Satellite Image Time Series for land cover mapping via a multi-source deep learning architecture. *ISPRS Journal of Photogrammetry and Remote Sensing*, 158: 11–22.
- Jin, Y.; Liu, X.; Chen, Y.; and Liang, X. 2018. Land-cover mapping using Random Forest classification and incorporating NDVI time-series and texture: A case study of central Shandong. *International journal of remote sensing*, 39(23): 8703–8723.
- Jin, Z.; Azzari, G.; You, C.; Di Tommaso, S.; Aston, S.; Burke, M.; and Lobell, D. B. 2019. Smallholder maize area and yield mapping at national scales with Google Earth Engine. *Remote sensing of environment*, 228: 115–128.
- Kehe, A.; McCloskey, P.; Chelal, J.; Morr, D.; Amakove, S.; Plimo, B.; Mayieka, J.; Ntango, G.; Nyongesa, K.; Pamba, L.; Jeptoo, M.; Mugo, J.; Tsuma, M.; Mukami, W.; Onyango, W.; and Hughes, D. 2021. From Village to Globe: A Dynamic Real-Time Map of African Fields Through PlantVillage. *Frontiers in Sustainable Food Systems*, 5.
- Kerner, H. 2020. Too many AI researchers think real-world problems are not relevant. *Opinion. MIT Technology Review*.
- Kerner, H.; Tseng, G.; Becker-Reshef, I.; Nakalembe, C.; Barker, B.; Munshell, B.; Paliyam, M.; and Hosseini, M. 2020. Rapid Response Crop Maps in Data Sparse Regions. In *ACM SIGKDD Conference on Data Mining and Knowledge Discovery Workshops*.
- Kpienbaareh, D.; Sun, X.; Wang, J.; Luginaah, I.; Bezner Kerr, R.; Lupafya, E.; and Dakishoni, L. 2021. Crop Type and Land Cover Mapping in Northern Malawi Using the Integration of Sentinel-1, Sentinel-2, and PlanetScope Satellite Data. *Remote Sensing*, 13(4).
- Kussul, N.; Lavreniuk, M.; Skakun, S.; and Shelestov, A. 2017. Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data. *IEEE Geosci. Remote Sens. Lett.*, 14(5): 778–782.
- Lacuna Fund. 2020. Request for Proposals: Labeled Datasets for Agriculture in Sub-Saharan Africa.
- Leroux, L.; Jolivot, A.; Be'gue', A.; Seen, D.; and Zoungrana, B. 2014. How Reliable is the MODIS Land Cover Product for Crop Mapping Sub-Saharan Agricultural Landscapes? *Remote Sens.*, 6(9): 8541–8564.
- Lesiv, M.; Fritz, S.; McCallum, I.; Buchhorn, M.; Smets, B.; Kerchova, R. V. D.; and Obersteiner, M. 2017. Evaluation of ESA CCI prototype land cover map at 20m Approved by. Li, W.; Fu, H.; Yu, L.; Gong, P.; Feng, D.; Li, C.; and Clinton, N. 2016. Stacked Autoencoder-based deep learning for remote-sensing image classification: a case study of African land-cover mapping. *Int. J. Remote Sens.*, 37(23): 5632–5646.
- Li, X.-Y.; Li, X.; Fan, Z.; Mi, L.; Kandakji, T.; Song, Z.; Li, D.; and Song, X.-P. 2022. Civil war hinders crop production and threatens food security in Syria. *Nature Food*, 1–9.
- Liboiron, M. 2021. Decolonizing geoscience requires more than equity and inclusion. *Nature Geoscience*, 14(12): 876–877.
- Liu, E.; Gold, K. M.; Combs, D.; Cadle-Davidson, L.; and Jiang, Y. 2021. Deep learning-based autonomous downy mildew detection and severity estimation in vineyards. In *2021 ASABE Annual International Virtual Meeting*, 1. American Society of Agricultural and Biological Engineers.
- Lobell, D. B. 2013. The use of satellite data for crop yield gap analysis. *Field Crops Research*, 143: 56–64.
- Lobell, D. B.; Azzari, G.; Burke, M.; Gourlay, S.; Jin, Z.; Kilic, T.; and Murray, S. 2018. Eyes in the Sky, Boots on the Ground Assessing Satellite- and Ground-Based Approaches to Crop Yield Measurement and Analysis in Uganda.
- Lobell, D. B.; Thau, D.; Seifert, C.; Engle, E.; and Little, B. 2015. A scalable satellite-based crop yield mapper. *Remote Sensing of Environment*, 164: 324–333.
- Manziona, R. L.; and Matulovic, M. 2021. Decision-Making in Groundwater Management: Where Artificial Intelligence Can Really Lead Geoscientists? In *Adv. Sci. Technol. Innov.*, 441–445. Springer Nature.
- Maskey, M.; Alemohammad, H.; Murphy, K.; and Ramachandran, R. 2020. Advancing AI for Earth science: A data systems perspective. *Eos*, 101.
- Masoud, K. M.; Persello, C.; and Tolpekin, V. A. 2019. Delineation of Agricultural Field Boundaries from Sentinel-2 Images Using a Novel Super-Resolution Contour Detector Based on Fully Convolutional Networks. *Remote Sens.*, 12(1): 59.
- Meyer, L.; Lemarchand, F.; and Sidiropoulos, P. 2020. A Deep Learning Architecture For Batch-mode Fully Automated Field Boundary Detection. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.*, XLIII-B3-2(B3): 1009–1016.
- Mirik, M.; Ansley, R. J.; Price, J. A.; Workneh, F.; and Rush, C. M. 2013. Remote monitoring of wheat streak mosaic progression using sub-pixel classification of Landsat 5 TM imagery for site specific disease management in winter wheat.
- Mrisho, L. M.; Mbilinyi, N. A.; Ndalawa, M.; Ramcharan, A. M.; Kehe, A. K.; McCloskey, P. C.; Murithi, H.; Hughes, D. P.; and Legg, J. P. 2020. Accuracy of a Smartphone-Based Object Detection Model, PlantVillage Nuru, in Identifying the Foliar Symptoms of the Viral Diseases of Cassava—CMD and CBSD. *Front. Plant Sci.*, 11: 1964.
- Nabende, P.; Kabiito, D.; Babirye, C.; Tusiime, H.; and Nakatumba-Nabende, J. 2021. Misinformation detection in Luganda-English code-mixed social media text.
- Nakalembe, C. 2020. Urgent and critical need for sub-Saharan African countries to invest in Earth observation-based agricultural early warning and monitoring systems. *Environ. Res. Lett.*, 15(12): 121002.
- Nakalembe, C.; Becker-Reshef, I.; Bonifacio, R.; Hu, G.; Humber, M. L.; Justice, C. J.; Keniston, J.; Mwangi, K.; Rembold, F.; Shukla, S.; Urbano, F.; Whitcraft, A. K.; Li, Y.; Zappacosta, M.; Jarvis, I.; and Sanchez, A. 2021a. A review of satellite-based global agricultural monitoring systems available for Africa. *Glob. Food Sec.*, 29(January): 100543.

- Nakalembe, C.; Becker-Reshef, I.; Bonifacio, R.; Hu, G.; Humber, M. L.; Justice, C. J.; Keniston, J.; Mwangi, K.; Rembold, F.; Shukla, S.; Urbano, F.; Whitcraft, A. K.; Li, Y.; Zappacosta, M.; Jarvis, I.; and Sanchez, A. 2021b. A review of satellite-based global agricultural monitoring systems available for Africa.
- Olsen, V. M.; Fensholt, R.; Olofsson, P.; Bonifacio, R.; Butsic, V.; Druce, D.; Ray, D.; and Prishchepov, A. V. 2021. The impact of conflict-driven cropland abandonment on food insecurity in South Sudan revealed using satellite remote sensing. *Nature Food*, 2(12): 990–996.
- O’Neil, C. 2016. *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown. Onyango, C. M.; Nyaga, J. M.; Wetterlind, J.; So’derstro’m, M.; and Piikki, K. 2021. Precision Agriculture for Resource Use Efficiency in Smallholder Farming Systems in Sub-Saharan Africa: A Systematic Review. *Sustainability*, 13(3): 1158.
- Persello, C.; Tolpekin, V.; Bergado, J.; and de By, R. 2019. Delineation of agricultural fields in smallholder farms from satellite images using fully convolutional networks and combinatorial grouping. *Remote Sensing of Environment*, 231: 111253.
- Planet, Inc. 2021. NICFI Data Program User Guide. Potapov, P.; Turubanova, S.; Hansen, M. C.; Tyukavina, A.; Zalles, V.; Khan, A.; Song, X.-P.; Pickens, A.; Shen, Q.; and Cortez, J. 2021. Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. *Nat. Food*, 3(January).
- Qin, Z.; and Zhang, M. 2005. Detection of rice sheath blight for in-season disease management using multispectral remote sensing. *Int. J. Appl. Earth Obs. Geoinf.*, 7(2): 115–128.
- Qin, Z.; Zhang, M.; Christensen, T.; Li, W.; and Tang, H. 2003. Remote Sensing Analysis of Rice Disease Stresses for Farm Pest Management Using Wide-band Airborne Data. In *Int. Geosci. Remote Sens. Symp.*, volume 4, 2215–2217.
- Rolnick, D.; Donti, P. L.; Kaack, L. H.; Kochanski, K.; Lacoste, A.; Sankaran, K.; Ross, A. S.; Milojevic-Dupont, N.; Jaques, N.; Waldman-Brown, A.; Luccioni, A.; Maharaj, T.; Sherwin, E. D.; Mukkavilli, S. K.; Kording, K. P.; Gomes, C.; Ng, A. Y.; Hassabis, D.; Platt, J. C.; Creutzig, F.; Chayes, J.; and Bengio, Y. 2019. Tackling Climate Change with Machine Learning.
- Rostaminia, M.; Rahmani, A.; Mousavi, S. R.; Taghizadeh-Mehrjardi, R.; and Maghsodi, Z. 2021. Spatial prediction of soil organic carbon stocks in an arid rangeland using machine learning algorithms. *Environ. Monit. Assess.*, 193(12).
- Rubanga, D. P.; Loyani, L. K.; Richard, M.; and Shimada, S. 2020. A deep learning approach for determining effects of Tuta Absoluta in tomato plants. *arXiv preprint arXiv:2004.04023*.
- Rustowicz, R.; Cheong, R.; Wang, L.; Ermon, S.; Burke, M.; and Lobell, D. 2019. Semantic segmentation of crop type in Africa: A novel dataset and analysis of deep learning methods. *IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work.*, 2019-June: 75–82.
- Sadeh, Y.; Zhu, X.; Dunkerley, D.; Walker, J.; and Chenu, K. 2021. Wheat yield estimation using fused Cubesat and Sentinel-2 imagery. In *Precision agriculture '21*, 1–14. Wageningen Academic Publishers.
- Sahajpal, R.; Becker-Reshef, I.; and Coutu, S. 2020. Optimizing Crop Cut Collection for Determining Field-Scale Yields in an Insurance Context.
- Sahajpal, R.; Fontana, L.; Lafluf, P.; Leale, G.; Puricelli, E.; O’Neill, D.; Varela, M.; and Becker-Reshef, I. 2020. Operationalizing earth observation based machine-learning models for field-scale crop yield forecasting. In *AGU Fall Meeting Abstracts*.
- Samberg, L. H.; Gerber, J. S.; Ramankutty, N.; Herrero, M.; and West, P. C. 2016. Subnational distribution of average farm size and smallholder contributions to global food production. *Environ. Res. Lett.*, 11(12).
- Sanga, S.; Mero, V.; Machuve, D.; and Mwanganda, D. 2020. Mobile-Based Deep Learning Models for Banana Diseases Detection. *arXiv preprint arXiv:2004.03718*.
- Sasson, A. 2012. Food security for Africa: An urgent global challenge.
- Savage, N. 2020. The race to the top among the world’s leaders in artificial intelligence. *Nature*, 588(7837): S102–S102.
- Skakun, S.; Kussul, N.; Shelestov, A.; and Kussul, O. 2016. The use of satellite data for agriculture drought risk quantification in Ukraine. *Geomatics, Nat. Hazards Risk*, 7(3): 901–917.
- Song, X.-P.; Potapov, P. V.; Krylov, A.; King, L.; Di Bella, C. M.; Hudson, A.; Khan, A.; Adusei, B.; Stehman, S. V.; and Hansen, M. C. 2017. National-scale soybean mapping and area estimation in the United States using medium resolution satellite imagery and field survey. *Remote Sensing of Environment*, 190: 383–395.
- Tseng, G.; Kerner, H.; Nakalembe, C.; and Becker-Reshef, I. 2021a. Learning To Predict Crop Type From Heterogeneous Sparse Labels Using Meta-Learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- Tseng, G.; Zvonkov, I.; Nakalembe, C.; and Kerner, H. 2021b. CropHarvest: a global satellite dataset for crop type classification. In *Neural Information Processing Systems (NeurIPS) Datasets and Benchmarks Track*.
- Tusubira, J. F.; Nsumba, S.; Ninsiima, F.; Akera, B.; Acellam, G.; Nakatumba, J.; Mwebaze, E.; Quinn, J.; and Oyana, T. 2020. Improving In-field Cassava Whitefly Pest Surveillance with Machine Learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 68–69.
- Waldner, F.; and Diakogiannis, F. I. 2020. Deep learning on edge: Extracting field boundaries from satellite images with a convolutional neural network. *Remote Sensing of Environment*, 245: 111741.
- Wang, A. X.; Tran, C.; Desai, N.; Lobell, D.; and Ermon, S. 2018. Deep Transfer Learning for Crop Yield Prediction with Remote Sensing Data. In *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies (COMPASS)*.
- Wang, S.; Di Tommaso, S.; Deines, J. M.; and Lobell, D. B. 2020. Mapping twenty years of corn and soybean across the US Midwest using the Landsat archive. *Sci. Data*, 7(1): 307.
- Wang, S.; Waldner, F.; and Lobell, D. B. 2022. Unlocking large-scale crop field delineation in smallholder farming systems with transfer learning and weak supervision. *arXiv preprint arXiv:2201.04771*.
- Whitcraft, A. K.; Becker-Reshef, I.; Justice, C. O.; Gifford, L.; Kavvada, A.; and Jarvis, I. 2019. No pixel left behind: Toward integrating Earth Observations for agriculture into the United Nations Sustainable Development Goals framework. *Remote Sens. Environ.*, 235:

111470.

World Bank. 2021. World Bank Open Data.

World Bank Group. 2019. *Toward Scaled-Up and Sustainable Agriculture Finance and Insurance in Uganda*. World Bank, Washington, DC.

Xiong, J.; Thenkabail, P.; Tilton, J.; Gumma, M. K.; Teluguntla, P.; Congalton, R.; Yadav, K.; Dungan, J.; Oliphant, A.; Poehnel, J.; Smith, C.; and Massey, R. 2017. NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security-support Analysis Data (GFSAD) Cropland Extent 2015 Africa 30 m V001.

Yang, C.; and Everitt, J. H. 2011. Remote sensing for detecting and mapping whitefly (*Bemisia tabaci*) infestations. In *The Whitefly, Bemisia tabaci (Homoptera: Aleyrodidae) Interaction with Geminivirus-Infected Host Plants*, 357–381. Springer.

You, J.; Li, X.; Low, M.; Lobell, D.; and Ermon, S. 2017. Deep Gaussian Process for Crop Yield Prediction Based on Remote Sensing Data. *Proceedings of the AAAI Conference on Artificial Intelligence*.

Zanaga, D.; Van De Kerchove, R.; De Keersmaecker, W.; Souverijns, N.; Brockmann, C.; Quast, R.; Wevers, J.; Grosu, A.; Paccini, A.; Vergnaud, S.; Cartus, O.; Santoro, M.; Fritz, S.; Georgieva, I.; Lesiv, M.; Carter, S.; Herold, M.; Li, L.; Tsendbazar, N.-E.; Ramoino, F.; and Arino, O. 2021. ESA World Cover 10 m 2020 v100.

Zhang, Y.; Chipanshi, A.; Daneshfar, B.; Koiter, L.; Champagne, C.; Davidson, A.; Reichert, G.; and Be´dard, F. 2019. Effect of using crop specific masks on earth observation based crop yield forecasting across Canada. *Remote Sens. Appl. Soc. Environ.*, 13: 121–137.