Monitoring Climate and Environmental Effects on Agriculture and Food Security Using Geospatial Artificial Intelligence (Geo AI) Technologies

Deci Raisa Lim, Colin Vu, Aasa Dommalapati
Georgia Institute of Technology Atlanta, GA
dhermosilla3@gatech.edu, cvu33@gatech.edu, adommalapati6@gatech.edu

Abstract: This paper gives an overview of two geospatial artificial intelligence (Geo AI) technologies that are used to examine agricultural land conditions, climate, and environmental changes in relation to food security. We discuss the advantages of the IBM Environmental Suite and the Prithvi Multitemporal Crop Detection Model and give some general insight on the necessity of using geo AI for addressing issues related to food security and its four main indicators: accessibility, availability, affordability, and utilization. As Geo AI is an emerging field, there have not been many real-world applications or innovative solutions to help local stakeholders such as farmers utilize these newer technologies in addressing local issues and needs as they arise in agricultural practices and locations. The IBM Environmental Suite and the Prithvi Multitemporal Crop Detection Model are opening new ways to help more stakeholders adapt these applications and create solutions to help address food security issues in more localized areas.

Keywords: Geo AI, Geospatial technologies, Geographic information systems, Artificial intelligence, Crop monitoring, Climate solutions, Climate innovation

1 Introduction

According to a report by the Food and Agriculture Organization of the United Nations (FAO), the International Fund for Agricultural Development (IFAD), the United Nations Children's Fund (UNICEF), the World Food Program (WFP), and the World Health Organization (WHO), global food security is projected to worsen due to rapid population growth, overexploitation of soil and land, the depletion of natural resources, and climate change. To address these challenges, the application of AI models and Geo AI to examine indicators and intricate relationships between social, economic, and environmental factors that affect food security is now imperative (Sarku e. al, 2023).

With the rapid advancements in AI and in computing hardware, the field of geospatial artificial intelligence (Geo AI) has emerged to address the need for analyzing changes in lands, crops, climate, and the environment, especially in difficult to reach or inaccessible areas across the globe. This study reviews two new Geo AI tools from IBM and NASA that can address the problems and challenges in monitoring climate, environmental, economic, and geopolitical effects on food security.

Geo AI is essential to determining and reducing risks caused by climate variability and helping improve the efficiency of agricultural production which are important for farmers and food security around the world. According to Sarku et. al., as of 2023, studies on AI models for food security have been primarily experimental and lacking in real-life implementations. There is often a failure in effectively translating these models into actionable policies and usable software for local communities.

In August 2023, IBM & NASA released an open source Geospatial AI Foundation model, called the Prithvi Multitemporal Crop Detection. This model is pre-trained and fine tuned to classify crop and other land cover types based on Harmonized Landsat Sentinel-2 (HLS) data and Cropland Data Layer (CDL) labels.

Another Geo AI tool in recent development is IBM's Environmental Suite, which has been demonstrated to help stakeholders such as smallholder farmers access to weather data, agronomic data, and carbon footprint calculations that facilitate production management and allow better adaptation to climate change (IBM, 2023).

This paper aims to provide a high-level understanding of the features and advantages of using Geo AI to gain insights on the status of agricultural lands, climate and environmental, and effects of geopolitical conflict in relation to food security. The following questions will be addressed in the subsequent sections:

- What are the issues regarding food security that Geo AI can be applied to?
- What features of Geo AI can be utilized to help identify and provide solutions for problems regarding food security?
- What is the state of Geo AI technologies and how have they been applied to help stakeholders (organizations, small farmholders, agribusinesses, etc.)?

2 Technologies

In early 2023, IBM released two significant applications that utilize geo AI technologies, allowing smallholder farms in Costa Rica to create and customize a dashboard that address local issues in farming, agriculture, and food production. Pilot testing of the IBM Environmental Suite involved over 1,300 farmers in Ecuador, Colombia, Chile, and Argentina, as well as coordinating with a total of seven farm cooperatives. This solution has shown results in increasing the yields of crops such as coffee, yuca, bananas, and cacao (Silva, 2023).

2.1 IBM Environmental Intelligence Suite (IBM-EIS)

IBM's Environmental Suite is a cloud-based climate and sustainability platform that combines proprietary and third party geospatial, weather, environment, and IoT data to derive business insights (IBM-EIS, 2023). This suite offers customization for specific use cases such as vegetation management, weather safety, risk management, and sustainability strategy.

As a leading figure in geospatial analysis with its ownership of the Weather Company, IBM is uniquely qualified to provide detailed climate assessment data (IBM, 2023). This suite is primarily marketed towards organizations to assess asset damage due to climate impact and to gauge resources that may be affected by environmental growth and future climate change. It also estimates the regional benefits of renewables and encourages public safety using its climate modeling.

Each use case has its own set of data visualization tools; for instance, its vegetation management tool allows the user to select specific road segments and gives data about its area covered by vegetation, average height of vegetation, and weighted "priority" rating assessing its need for more or less vegetation. (IBM, 2023)

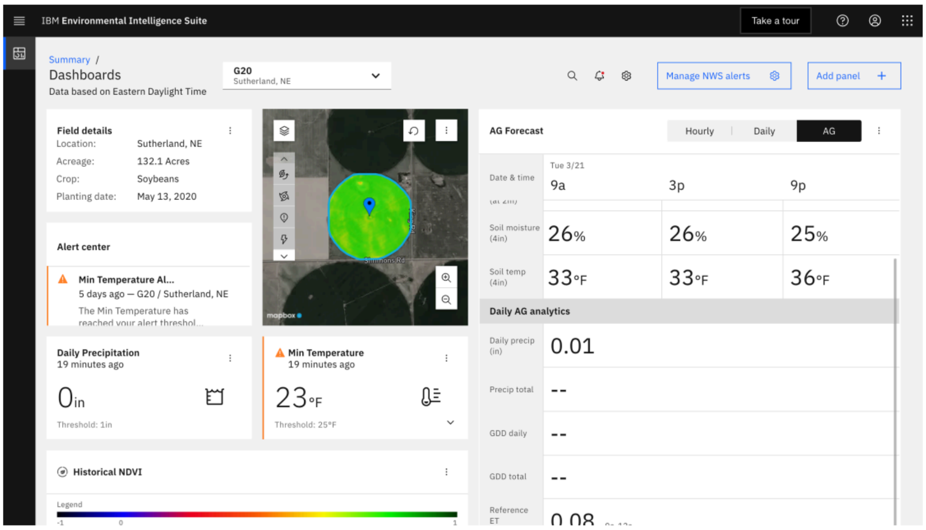

Figure 1. Example interface of the Environmental Suite modified for agricultural monitoring. This interface shows the user field details, precipitation and temperature

levels, forecasts, and historical Normalized difference vegetation indices (NDVI) (IBM, 2023).

2.2 IBM-EIS Development and Cost

As of December 2023, the IBM-EIS is still under beta development despite being rolled out to a few testers and some collaborative projects with organizations such as Plan21 in Latin America (Silva, 2023). Although IBM allows free trials of this software for individual users, it is not free for organizations who aim to customize the dashboards according to their needs.

In the trial version, only a preset of features are available and are shown depending on the use case. For the paid version, IBM offers three tiers: essentials, standard, and premium. Although each tier comes with a plethora of usable features, the more specific ones to agricultural management for precision and crop health are only available to the two latter price points. This may be an issue for smaller stakeholders or those in less developed regions that want to utilize better technology to accelerate their agricultural production and farming needs to help increase yield, supply, and address food security issues in their area.

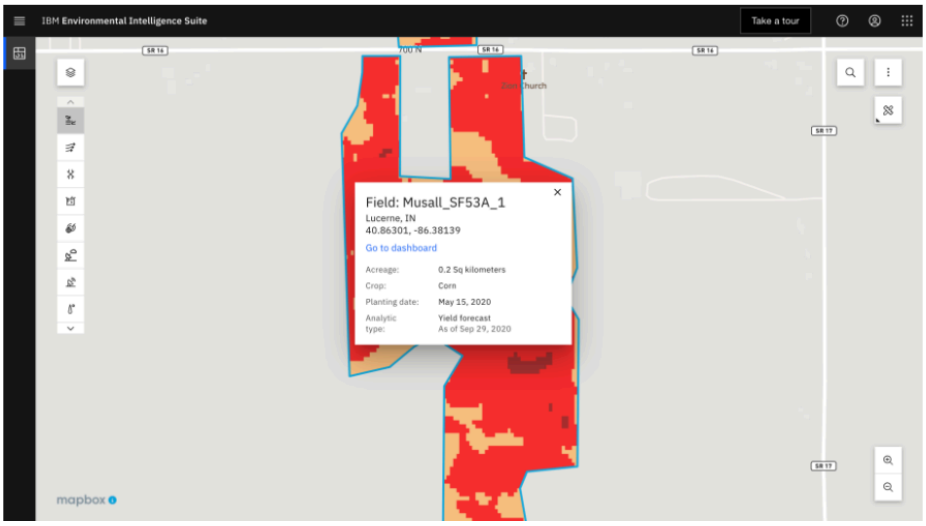

Figure 2. Crop yield forecast and prediction sample.

2.3 IBM-NASA Prithvi Crop Classification Model

Created jointly by NASA and IBM, Prithvi is a machine learning model that returns a detailed assessment of land uses, flood risk, wildfire history, and crop classification (IBM NASA Geospatial, 2023) of an area based on satellite imagery data gathered among six categories: three color categories (RGB), narrow near infrared radiation, and two shortwave infrared radiation measures. Each of these spectral bands are used to determine and predict the types of crops in an area and the changes during different seasons.

These models are integrated into the IBM Environmental Intelligence Suite (Martineau, 2023). Although the suite requires payment, the Geospatial Foundation Models from which the Prithvi Multitemporal Crop Classification is based, are fully open source. While the suite is considered a commercial version of Prithvi, the latter is strictly designed for high-level research (Martineau, 2023). Prithvi is considered the largest open source Geospatial AI Foundation Model in the world as of recent (Cecil et. al., 2023).

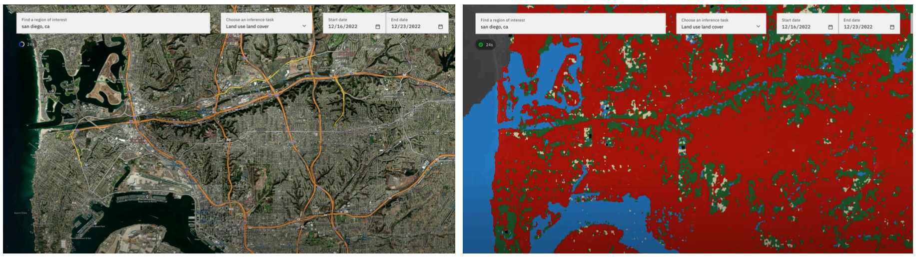

Figure 3. Display of the land use identification model in practice. Right image is a satellite map of San Diego, CA. Left image is an interpretation of land uses in the region based on HLS data (IBM, 2023).

Table 1. Major crop classifications of the Prithvi model. Intersection over Union (IoU), is the amount of intersection between predicted data and real data. Acc is a strict gauge of what percent of a given type of cropland was accurately identified (IBM, 2021).

Classes	**IoU**	**Acc**
Natural Vegetation	0.4038	46.89%
Forest	0.4747	66.38%
Corn	0.5491	65.47%
Soybeans	0.5297	67.46%
Wetlands	0.402	58.91%
Developed/Barren	0.3611	56.49%
Open Water	0.6804	90.37%

Winter Wheat	0.4967	67.16%
Alfalfa	0.3084	66.75%
Fallow/Idle Cropland	0.3493	59.23%
Cotton	0.3237	66.94%
Sorghum	0.3283	73.56%
Other	0.3427	47.12%

Source: IBM, 2021

2.4 Prithvi Data Preparation

While large geospatial datasets offer opportunities for training AI models, challenges arise in handling diverse data sources. Using different heterogeneous data sources requires an analysis of geographic location, often using Geographic Information Systems (GIS) tools. Along with the type and size of the datasets, another challenge is the necessity of high-performance computing hardware. Data preparation requires some in-depth knowledge of processing GeoTiff images from NASA's Harmonized Landsat and Sentinel-2 (HLS). Due to limited documentation that exists on preparing the data for the Prithvi models, there has been no known real-life application of this model to date (this model was released on August 3, 2023).

According to the existing documentation by Dr. Hamed Alemohammad from the Clark University Center for Geospatial Analytics (CGA), the Prithvi crop model takes in 6 bands of spectral data, compounded across three different seasons, resulting in one 18-band GeoTIFF file. Although the documentation describes these needed changes, it does not provide the specific detail of instruction to achieve the correct conversion of the data into "chips" of GeoTIFF files that the model itself requires in order to be trained or fine-tuned for areas outside of the United States. From the repository of the Dr. Alemohammad's team that prepared the foundation model's dataset, it is said that the "chips" are subdivided GeoTIFF images, unfortunately, they do not go into detail as to how the GeoTIFF images were subdivided and why.

In theory, all the data required to utilize Prithvi is publicly available. NASA's AppEEARS site allows requests to download GeoTIFF data from Sentinel-2 consisting of individual bands that may be combined (National Aeronautics and Space Administration, 2023). However, the lack of documentation about how bands are organized within the file, as well as our lack of professional understanding about the model make *Prithvi* difficult to utilize, especially by parties such as small farmholders who may benefit most from the information provided by Prithvi.

Other potential ways of preparing the needed data for the Prithvi model is by using MATLAB, ArcGIS, or some other GIS that could extract, combine, layer, and divide bands of HLS data into GeoTIFF chips. (Abdrakhimov, 2022) However, these methods too lack the proper documentation to use without a professional understanding of the software involved.

2.5 Limitations of Geo AI as a Practice

Furthermore, AI and ML models are known to hold inherent biases that limit the functionality of their usages. 60% of all geo-locatable images in the Open Images dataset commonly used for Geo AI models come from six highly developed countries. 1% and 2% come from China and India respectively, which when combined hold 40% of the world population (Janowitz, 2023). As a result, patterns recognized by machine learning models may be erroneous due to the lack of representative data.

3 Research Questions

In relation to the features that the two discussed technologies can provide, below are some questions that this paper aims to provide insight for..

3.1 What are the issues regarding food security that Geo AI can be applied to?

According to the World bank, food security is defined as "when all people have physical and economic access to safe, sufficient, and nutritious food that meets their dietary needs and food preferences for an active and healthy life." The four indicators of food security are accessibility, availability, affordability, and utilization.

A study by Sarku et. al. details 171 documents analyzing AI-based solutions to issues in the space of food security and found that 105 focused on food production, which represents food availability, 35 applied AI models to assess disparities in food distribution among households which represents accessibility, and the rest were thinly spread among topics that talked about affordability and utilization. This means that not all current studies using geospatial technologies or Geo AI related solutions are equally addressing the issues of food security.

Broadly, Geo AI allows us to create a thorough and predictive analysis of land conditions and food sources. Crops, cattle, vegetation, etc. require large amounts of land to produce food productively (Sarku 2023).

Geo AI can also monitor crop health, identify diseases, and optimize agricultural practices. This contributes to increased food production, addressing the challenge of food availability. It also provides insights into climate patterns, helping farmers adapt to changing conditions. This adaptation is crucial for mitigating the impact of climate change on crops and ensuring consistent food production. Along with these issues, Geo AI also helps optimize water usage in agriculture by monitoring water availability and irrigation needs. Efficient water resource management contributes to sustainable farming practices and addresses concerns of water scarcity (Roy, 2023).

3.2 What features of Geo AI can be utilized to help identify and provide solutions for problems regarding food security?

Geo AI allows us to gain an understanding of land conditions remotely and on a more timely, if not, real-time basis. It is used to identify weather patterns, soil health, rain density, geological shifts, and the effects of geopolitical conflicts (Ma, 2022). Based on these metrics, policies and new software can be made to identify how to sustainably allocate farmland for productivity and increase crop yields.

With the right customization for specific stakeholder needs, Geo AI technology allows users to optimize agricultural practices by aiding farmers in making more informed decisions about planting and harvesting times, maximizing crop yields. It also enhances soil management which guides farmers in adopting precise soil management practices, leading to improved crop health and increased agricultural productivity (Sarku, et. al.). Geo AI could potentially utilize efficient water resources through monitoring rain density and identify geological and environmental risks such as landslides and soil erosion (Trivedi, 2023).

For instance, Prithvi's crop detection model may allow organizations to identify the distribution of different crops on a larger scale and without having the need to go to certain areas that are difficult to reach by human means. If cross-referenced with data concerning farm productivity, a farmholder can identify which areas tend to be more productive for yielding specific crops and can adjust farms accordingly. By maximizing productivity of crop production, food security can increase.

Among the IBM Environmental Suite's list of tools is a vegetation growth model that projects the vegetation behavior of a region over a period of time. This feature would allow stakeholders to predict their yield or a season and can then identify how they would distribute or utilize any other parts of the land during that time. It can serve as an essential tool for planning the maintenance of agricultural regions and identifying productivity/resources for different seasons and climate.

3.3 What is the state of Geo AI technologies and how have they been applied to help stakeholders (organizations, small farmholders, agribusinesses)?

GeoAI research into the effects of environmental damage on the condition of agricultural lands has been completed in the past, and this information can be used to inform policy changes.

In a 2021 study, Papagiannisa, Gazzolab, Burakc, and Pokutsa propose solutions to improve Ukraine's poor waste management conditions. The extent of conditions is determined by a machine learning model that analyzes current residual waste levels, similar to other European countries.

In the event that satellite data-based models measuring cropland conditions, especially land damage, do not yield usable results, an approach similar to Papagiannisa et al. may be used to dictate which agricultural regions have suffered more environmental damage, and how resources to each should be allocated. (Papagiannisa et al., 2021).

Regardless, an important use of GeoAI tools in the analysis of environmental damage is to predict behavior of an event before it occurs. The same study concludes that "a proactive rather than a reactive" approach to cleaning waste damage–and therefore environmental land damage–is necessary to prevent further residual damage from affecting the region (Papagiannisa et al., 8). The purpose of predictive GeoAI analysis of agricultural lands is to understand and model the trajectory of damage conditions in a region early so that the best approach can be used as soon as possible to mitigate the damage caused. Otherwise, a "reactive" approach may allow poor conditions to fester and result in less usable agricultural lands, thus increasing the rate of food insecurity in the region.

While there have been several Geo AI models created through research and by organizations, the study by Sarku et. al. identifies caveats towards its usage as it pertains to local businesses.

- There has been limited involvement from small farmholders and local communities and organizations in the creation and use of Geo AI models. (Sarku et. al., 2023)
- Small farmholders produce one-third of the world's food supply but do not get assistance in sustainably increasing

food security due to their lack of involvement in the creation of technologies (Silva, 2023).

- The creation of Geo AI technologies is driven by capability of AI models rather than the requirements of needs of local stakeholders (Pluto-Kossakowska, 2021).

With the involvement of local stakeholders, Geo AI can drastically change the landscape of food security around the globe by providing accurate predictions and real-time climate, crop, and land data to quickly adapt to changes that can cause detrimental effects to crop yields and soil health (Silva, 2023).

Sarku et. al. highlight that the global application of Geo AI models needs to navigate the issue of scaling for different environments. Applications of Geo AI are primarily based on priorities set by international donor agencies concerning global food security and food systems. They feature a significant focus on areas such as climate-smart agricultural practices, agroecology, climate information services, and sustainable agricultural practices. This mirrors the global agenda for addressing challenges in the agricultural sector. However, these AI models often do not universally address all food security challenges due to the diversity of local conditions. There is a need to carefully navigate and balance the global ambition of AI solutions with the intricacies of local realities.

Collaboration between global and local stakeholders is essential. Local communities should have an active role in shaping the research agenda and adapting AI solutions to their specific needs.

4 Conclusions and Future Work

As food security and its challenges due to social, geopolitical, economic, and environmental impacts become more apparent, the need for technological advancements to help create solutions and address problems, such as Geo AI is becoming more imperative. Geo AI is an emerging technology with few real-world applications to date due to the complexity of processing data for training AI models and low involvement of stakeholders to train the models and create applications for their specific needs. By using Geo AI to support local stakeholders, we can address issues of food security in more local regions based on their needs and specific problems that is causing it. For example, smallholder farmers, who produce about one-third of the world's food supply, could be aided in using or creating technology that can help them identify issues and solutions for rain densities, soil health, and farming strategies in real-time to address supply and crop issues earlier and mitigate risks that lead to delayed production and distribution of food in local areas. Geo AI must be researched and used with the understanding that datasets are not collected fairly from geolocations, which results in inherent biases and inaccurate data.

IBM’s Environmental Intelligence Suite (EIS) provides an out-of-box solution for organizations and stakeholders to customize and tailor features of a dashboard and the information that they can use to monitor crops, yields, soil moisture levels, water retention, and climate changes in their areas. A full version of this software is available but is costly and may not be a sustainable solution for smaller stakeholders.

IBM and NASA's Geospatial AI Foundation model, specifically the Prithvi Multitemporal Crop Detection model/demo, is an open-source, pre-trained model. Its features can be further fine-tuned with stakeholders' own data. The model is free and can be used as a base for customized software, depending on the needs of the users. However, it currently lacks documentation about processing and preparing datasets for further training and fine-tuning.

Moving forward, significant progress can be made in Geo AI research–the field is very young with the technologies mentioned being released within the past year (2023), so breakthrough documentation and tools are currently in progress. IBM-EIS is fully releasing for public use with a date at the end of 2023 according to IBM Sustainability (personal communication, November 14th, 2023) and should see significant documentation in the following months.

In future work, research can be conducted in areas of interest identified by working closely with stakeholders such as small farmholders, agricultural communities, and those in communities affected by conflict. Research should develop a fundamental understanding of the stakeholders’ needs and the specific features of Geo AI that can aid their farming practices, crop distribution, and knowledge of lands and agronomy available to them in order to address specific areas of food (in)security in their regions and respective communities.

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