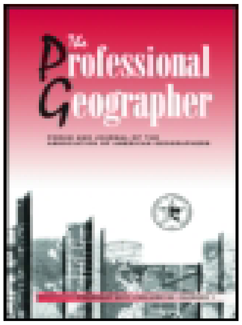

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A Geospatial Approach to Assessing the Impact of Agroecological Knowledge and Practice on Crop Health in a Smallholder Agricultural Context

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In the context of food insecurity in resource-poor settings, agroecology (AE) has emerged as an important approach promoted for improving crop productivity, yet few studies have demonstrated how a combination of agroecological methods can improve crop health and thereby crop productivity. Using a geospatial approach, this study investigated whether agroecological practices can improve crop health in smallholder contexts. We compared leaf area indexes (LAIs) of crops on AE and non-AE farms and prospectively predicted the impact of AE using vegetation indexes (VIs). We found that crops on AE farms produced higher average growing season LAIs for maize and pigeon peas ($1.28\,m^2/m^2$) and maize and beans ($1.29\,m^2/m^2$) farms compared to $0.97\,m^2/m^2$ and $0.80\,m^2/m^2$, respectively, for the same crops on the non-AE farms. The higher LAIs suggest that the combination of farming strategies practiced on the AE farms produced healthier crops on AE farms. Random forest regression prospective predictions generated statistically significant higher LAIs for maize and beans ($R^2 = 0.90$, root mean square error [RMSE] $= 0.32\,m^2/m^2$) and maize and pigeon peas ($R^2 = 0.88\,m^2/m^2$, RMSE $= 0.42\,m^2/m^2$) on the AE farms, but predictions for the non-AE farms were not statistically significant. The findings demonstrate that combining AE strategies can potentially improve crop productivity to enhance household food security and income in smallholder contexts. **Key Words: agroecology agroecosystems crop health Malawi random forest regression.**

Climate change, biodiversity loss, and food insecurity are three interrelated environmental challenges confronting humanity in the twenty-first century (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services 2019). The interacting impacts of these threats have contributed to current challenges with the agri-food system and the deteriorating global food insecurity situation (Food and Agriculture Organization [FAO] et al. 2019). Recent figures show that the global food-insecure population increased from 785.4 million in 2015 to 821.6 million in 2018, with locations plagued by drought, conflicts, civil wars, and natural hazards the most severely affected. In the Global South, these threats are further exacerbated by existing economic and structural vulnerabilities including poverty and social inequalities (FAO et al. 2018). The majority of the population most affected by food insecurity in the Global South are small- and medium-scale farmers who, paradoxically, also produce between 51 and 77 percent of the global food supply (Herrero et al. 2017) and sustain the food needs of about two-thirds of the more than 3 billion rural inhabitants worldwide (Rapsomanikis 2015).

Sub-Saharan Africa (SSA) is the region most disproportionately affected by food insecurity (FAO et al. 2019). Food insecurity is a major hindrance to the attainment of the Zero Hunger (Sustainable Development Goal 2) target (World Health Organization 2018). As such, the discourse on food insecurity has attracted significant attention in the public policy sphere. Many of the policies designed to address food insecurity aim to increase yield for food crops through technical and agrochemical fixes (Godfray and Garnett 2014), notably agricultural mechanization, heavy reliance on agrochemicals, and unrestrained expansion of agricultural lands. These techno-centric approaches to increasing crop yield are mostly favored by governments and neoliberal international organizations in the Global North and

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have been implemented through programs such as the new green revolution (Ingram 2011; Cabral 2019; Higgins 2020). These technological fixes have increased yields of some crop varieties in the Global North, notably maize and wheat. In some contexts, however, claims of increased production have been overstated (Messina, Peter, and Snapp 2017). Yet these technological approaches come with high environmental costs, including degraded agroecosystems and biodiversity loss (Aguilera Nuñez 2020; Morrison, Brosi, and Dirzo 2020), human health complications (Gordon et al. 2017), the erosion of traditional knowledge systems, and the disappearance of climate-resilient traditional seed varieties (Bezner Kerr 2014). These productivist approaches also require heavy investment in infrastructure and production systems (Gengenbach et al. 2018), which are mostly lacking in smallholder agriculture systems.

The challenge confronting policymakers and analysts is, thus, to identify ways to increase agricultural productivity more sustainably and equitably while ensuring the ecological integrity of the environment (Hodbod et al. 2016; Garbach et al. 2017). Agroecology (AE) has emerged as a pro-poor cost-effective alternative for increasing yields of diverse crops, enhancing the ecological functions of ecosystems, increasing the resilience of farms to external shocks (e.g., erratic rainfall and droughts), and ensuring autonomy without the need for external resources (Altieri 2009; Tamburini et al. 2020). AE is broadly defined as "the integrative study of the ecology of the entire food system, encompassing ecological, economic and social dimensions" (Francis et al. 2003). As a set of practices, AE works to ensure more resilient landscapes that preserve ecological processes and delivery of ecosystem services that are critical for crop production (Holt et al. 2016; Kpienbaareh et al. 2020), have short- and long-term benefits for farmers and the environment, and have climate change mitigation cobenefits (Kansanga et al. 2021).

Applying a blend of AE farming strategies including integrating natural and seminatural landscape elements, planting cover crops, using green manure, intercropping, and agroforestry, enriches the soil and facilitates pest management (Shennan, Gareau, and Sirrine 2012; Muchane et al. 2020). AE stresses the interrelatedness of all agroecosystem components and the complexity of ecological processes (Bover-Felices and Suarez-Hernandez 2020; Douglas et al. 2020). The emphasis on this interrelatedness implies that the success of agroecological methods in producing the desired result depends on their interaction with other farm management practices such as weed management and the timing of farm-level interventions such as weeding and application of pesticides. There are diverse frames of presenting AE—as a critical theory in agricultural science, as a practice of farmers and agriculturists, and as a social movement comprising many social actors interested in promoting it (Wezel et al. 2020).

In Malawi, where smallholder agriculture is predominant, there are questions about the feasibility of AE to replace conventional agriculture in the context of food insecurity and rapidly changing climate. Over the years, governments in Malawi have implemented the Farm Input Subsidy Program with policies that promote the use of synthetic fertilizers (Lunduka, Ricker-Gilbert, and Fisher 2013). The increased reliance on synthetic fertilizers in the country has not led to a commensurate increase in yield because synthetic fertilizers have not been successful in addressing underlying issues with soil erosion, deteriorating soil organic matter content, and declining soil microorganisms, which all affect soil health and ultimately crop health (Bi, Yao, and Zhang 2015; Campbell et al. 2017). There is also the additional challenge of farmers receiving fertilizers from government agencies at the wrong time of the growing season, which often works against crop yield (Momesso et al. 2022). About 39.7 percent of agricultural land in Malawi is degraded (Mbow et al. 2019), and more than 80 percent of the population reside in rural areas and also rely on agriculture and forest resources for their food, energy, and other livelihood needs. Poverty is disproportionately higher in these rural areas, however (World Bank 2019). Further, the majority of the population in Malawi is food insecure, with 40 percent of children under five years old facing chronic undernutrition (National Statistical Office 2017). These challenges call for farming strategies that address existing social inequalities and ecological challenges. Evidence suggests that integrating AE in farm management can yield important benefits for farms and the environment (Kpienbaareh et al. 2022). It is crucial, though, to monitor and assess the impact of combinations of various agroecological practices implemented on small farms on the growth and health of crops in resource-poor locations such as Malawi to identify context-specific agronomic practices for improving health sustainably.

Typically, monitoring and assessing the impact of agronomic practices on crop growth and health is conducted using field experiments. Although field experiments often produce accurate and generally applicable results (Adimassu et al. 2017; Romaneckas et al. 2019), such experiments are often limited in scope (the number of different farming practices that can be assessed simultaneously) and scale (the spatial extent of the area that can be monitored concurrently). Increasingly, the use of remote sensing techniques, including satellite and unmanned aerial vehicles (UAVs) to monitor, assess, and predict crop health, both retrospectively and prospectively (Danner et al. 2015; Harders et al. 2018; Cohrs et al. 2020), has gained significance with improvements in the spatial and temporal resolution of remote sensors. Most studies on monitoring and assessing crop health have been on monocropped, large-scale commercial farms, mainly in the Global North, where precision agriculture has become commonplace. Yet, it is important to monitor and assess crop health in smallholder agriculture systems in the Global South, where subsistence farming practiced on relatively smaller farmlands with mixed cropping systems is prevalent, to better understand the impacts of the combinations of different agronomic practices on crop growth and health to guide production decisions. The objective of this study is, therefore, to apply a remote sensing method to assess the impact of a combination of agroecological practices applied by smallholder farmers on crop growth and health. We compare leaf area indexes (LAIs) of farms managed with AE farming strategies with farms managed using conventional agricultural practices to assess the differential impacts of the different management practices on crop growth health. In this study, we define conventional farming to include the use of synthetic chemical fertilizers, pesticides, and hybrid seeds (Sumberg and Giller 2022). Because field experimental observations (Adimassu et al. 2017; Romaneckas et al. 2019) reveal that the type of farm management practices affects the biophysical properties of crops, we used LAIs to prospectively predict crop health to examine the seasonal impacts of agronomic management practices on crop health.

Materials and Methods

Study Area Description

This study was conducted in two village areas[1] in the Mzimba district in northern Malawi (Figure 1). The Mzimba district has a total land area of 10,430 km^2 (Government of Malawi 2018), with moderately fertile soils of a medium to light texture, mostly sandy-loam and loamy, with moderate to good drainage (Gama et al. 2014). The semitropical climatic type in the area is characterized by average monthly maximum rainy season temperatures ranging from 27 °C to 33 °C. In the dry season months, temperatures usually range from 0 °C to 10 °C, with June and July being the coldest months. The unimodal rainfall pattern starts in November or December and ends in April, with rainfall amounts ranging from 800 mm to 1,000 mm (Li et al. 2017). The rainfall pattern, duration of planting season, and soil characteristics, observed in soil maps and previous studies, in both village areas are similar (Snapp 1998; Gama et al. 2014), so crop growth patterns would likely be similar. As in other parts of Malawi, smallholder farming in the district is highly dependent on the unimodal rainfall pattern, making it persistently vulnerable to droughts resulting from erratic rainfall.

Over the years, the government s Farm Input Subsidy Program to address low productivity and food insecurity in the country has been largely unsuccessful (Messina, Peter, and Snapp 2017) because of inadequate access to these subsidized inputs and climate variability. Amid these continuing challenges with conventional farming and agriculture in general, a growing number of nonprofit organizations and some government agencies are advocating for a transformation of the food system to be less dependent on imported synthetic fertilizers and unsustainable land cultivation methods. Within this context, AE is emerging as an alternative approach because it shares several similarities with traditional farming methods and involves the use of locally available resources. In the context of these characteristics of the agricultural and social conditions of the area, we seek to examine how the application of agroecological practices contributes to the growing effort to transform the food system in smallholder farms.

Research Design

We compared AE farms (farms on which specific agroecological management strategies were implemented) and non-AE farms (farms on which conventional methods were implemented). The AE farms were based on an intervention called the Malawi Farmer-to-Farmer Agroecology (MAFFA) project. MAFFA intervention was implemented from 2012 to 2017 to use a participatory approach to AE to improve smallholder agriculture in a context where conventional agriculture has failed to achieve food security and food sovereignty (Nyantakyi-Frimpong et al. 2017). Participatory AE is an approach to practicing AE that involves the active participation of farmers in designing, implementing, and assessing agroecological farming strategies to improve yield through knowledge coproduction and sharing.

Conventional agriculture practiced in the study area involved the use of synthetic fertilizers to improve soil conditions and agrochemicals for controlling pesticides with the ultimate goal of increasing yield. To improve yield, the farmers relied on calcium ammonium nitrate 46:0:0 fertilizer and synthetic agrochemicals (mainly Confidor), acquired through the government s Farm Input Subsidies Program. These practices had been implemented on the farms for the last five years. As part of the practices of these conventional farmers, residue from the previous year was burned as a way of preparing the land for the impending season. The structure of soils on these farms was, therefore, likely broken down and microbial activities were inhibited (Doerr and Cerdà 2005).

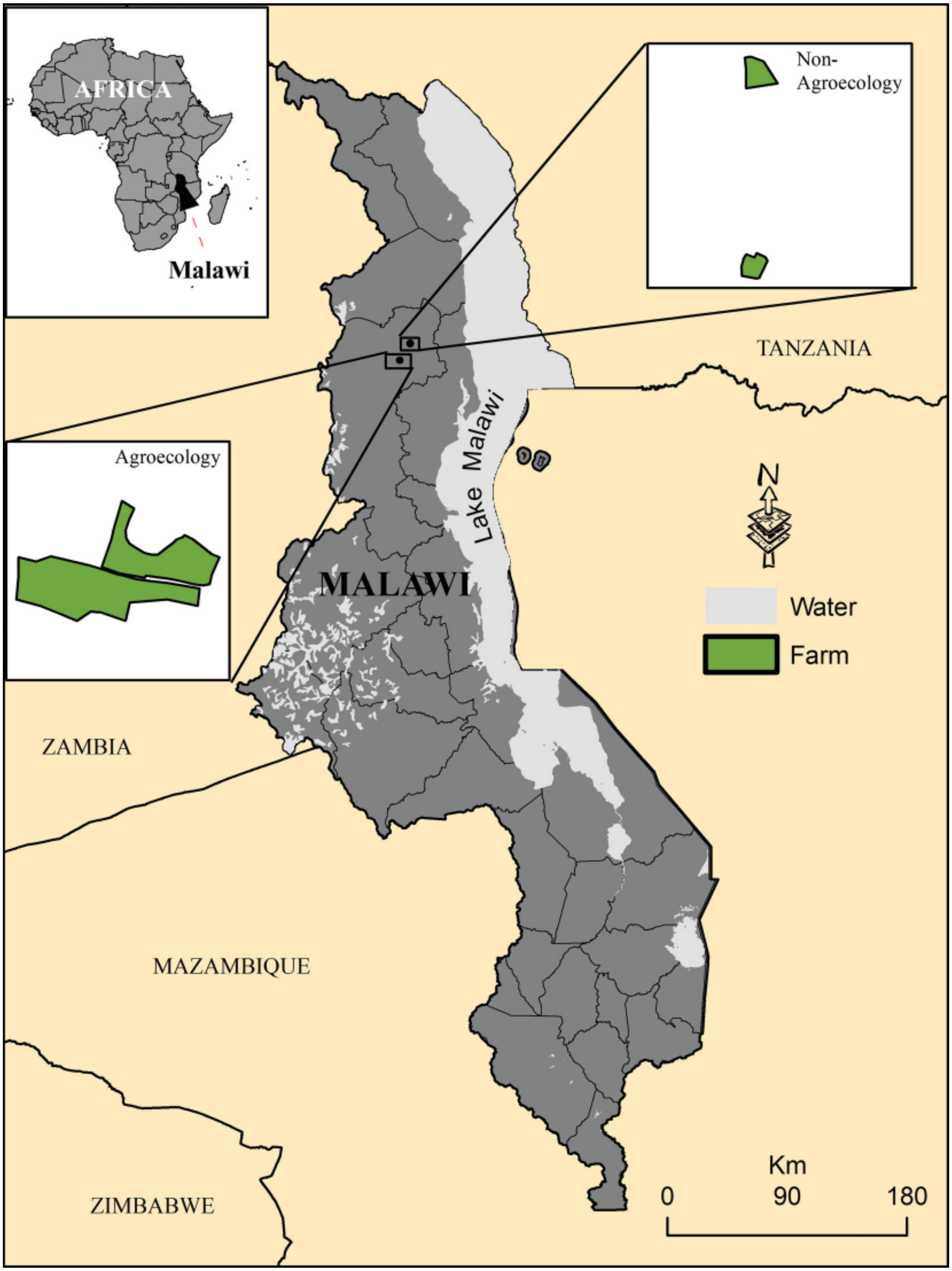

Figure 1 *Location of study areas. Four intercropped fields comprising two maize and pigeon pea and two maize and bean fields were selected from each study location. Fields 1 and 2 implemented agroecological management practices, whereas Fields 3 and 4 implemented conventional farming methods. Source of base map: ESRI.*

On the other hand, as part of the participatory AE practice, the farmers were trained on various sustainable soil management strategies including composting, crop residue burial, legume integration and intercropping, bokashi fertilizer application, agroforestry, and application of botanical pesticides (Kansanga et al. 2021). Composting during the study involved the use of converting farm residue, rotten fruits, and other household decomposable materials into organic fertilizers. These practices have been used by the farmers since the AE intervention was introduced. As such, there were long-term effects of the methods on the soils. Residue burial involved turning over residue from the previous season s harvest into the soil using hoes and covering it with soil before the first rains. The buried material decomposes and fertilizes the soil. Farmers planted leguminous and cereal crops on the same farm (legume integration or intercropping) to facilitate nutrient recycling and nitrogen fixation in the soil. For the maize bean intercrop, both crops were planted in the same stand whereas, for the pigeon peas, each crop was alternated with the other within the same row at 50 cm. Bokashi fertilizer was produced as an alternative fertilizer to synthetic fertilizer. Bokashi fertilizer is an organic fertilizer produced from manure, soil, maize bran, and either rotten fruits or commercial yeast for fermentation. Agroforestry practices among the farmers involved planting trees on farmlands, using trees they call fertilizer trees. These fertilizer trees, including *Gliricidia sepium*, are planted on current farmlands and their roots and fallen leaves. The botanical pesticides used in the study were prepared from *Tephrosia vogelii*, *Tithonia diversifiolia*, and *Vernonia amygdalina* for use in treating pest infestation. A recent study (Kpienbaareh et al. 2022) in the same location revealed that farmers had higher yields from small farmlands compared to non-AE farmers when implementing these agroecological farming methods. These AE intervention villages were selected based on several considerations, including the level of interest from the community members, limited involvement of other organizations in the area, and the level of food insecurity based on a baseline survey conducted at the start of the AE intervention by the research team (Bezner Kerr et al. 2016).

Selection of Farms

The two AE farms involved in this study provided a “typical” case of agroecological management, acknowledging that there would be some variation in practices across a wider set of cases. The criteria used to select the AE intervention villages were adopted to select the non-AE village for this comparative study to ensure similar baseline conditions for the two villages. A baseline survey was used to explore the socioeconomic conditions and food security status of the farmers. To avoid cross-contamination of the agroecological management strategies between the two villages, a buffer analysis was used to construct buffers at various intervals: 5 km, 10 km, 15 km, and >15 km around the AE intervention villages. The village area with the most similarities to the AE village area was approximately 18 km away and was chosen as the non-AE village area. Farmers from the village area were randomly selected from the community and farmers who consented had their farms included in the study. Because the study was focused on smallholder agriculture, only farms that were 2.0 ha or less in area (Lowder, Skoet, and Raney 2016) were included.

To ensure uniformity, the same crop cultivars were given freely to the participating farmers for planting. Sampling locations on the fields (shown in Figure 1) were identified on each farm, geolocated using Global Positioning System devices and labeled with letters. The geolocated coordinates in a .gpx file format were converted to point feature classes and stored in a file geodatabase, later exported to a .csv file format and used to extract vegetation indexes (VIs) computed from PlanetScope images. The extracted values were then used for machine learning regression analysis. To determine the number of sampling points on the farms, a grid of 5-m squares created in ArcGIS Pro was overlaid on the polygons of the farms and the squares were randomly selected such that the center point of each square is 10 m from the other. A sampling location was placed in each selected square and the canopies of crops were measured for use in computing the LAIs. The number of sampling points on each farm was determined by the area of the farm (in ha) to ensure proportionality and avoid duplication of the data collected. As such, although the number of samples might seem small, they represent the farm management practices that this study seeks to assess, making the result generalizable.

Data Collection

In Situ Field Measurements

Digital hemispherical photographs (DHPs) of crop canopies were captured using a Nikon D500 and an AF DX Fisheye-Nikkor lens for use in computing reliable estimates of in-situ LAIs. Measurements were conducted at weekly intervals from 24 December 2019 until the end of the season in April 2020 when LAIs natural tailed off. The timing of LAI collection dates was to ensure that phenological stages of crop growth are closely monitored. Sisheber et al. (2022) noted that the optimal time interval to collect LAI information for crops is eight days and concluded that this time interval is ideal for monitoring crop growth and development, hence their health. We also considered the amount of cloud cover in the atmosphere for field data collection because of the use of optical satellite remote sensing images, which are highly susceptible to cloud cover. Nine field sampling events took place at twenty-six selected sampling locations over the growing season. At each sampling location, fourteen DHPs were captured viewing vertically downward above the crop canopies within the 5-m square areas

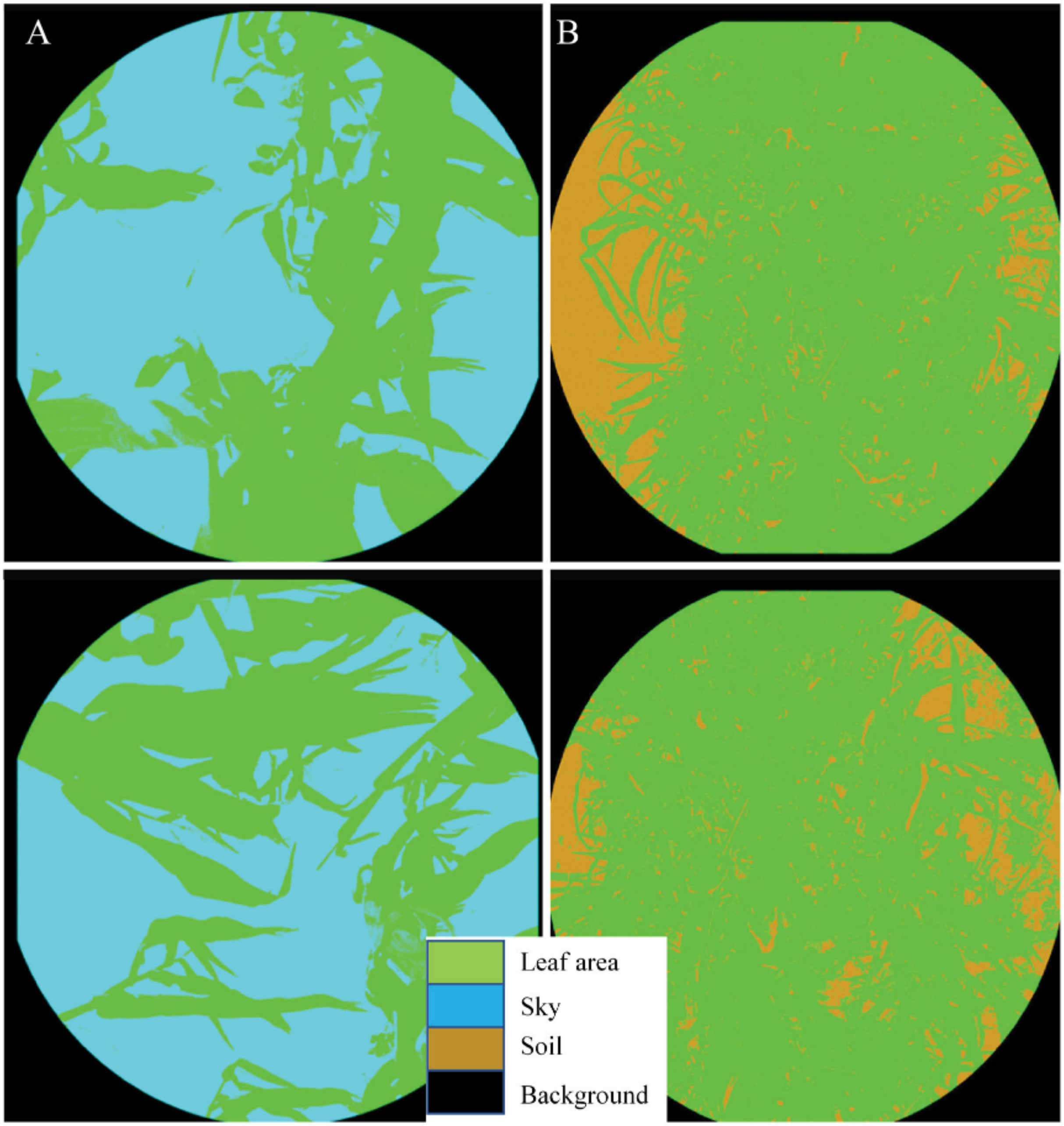

Figure 2 *Binarized output of image processor for A) upward-viewing, and B) downward-viewing digital hemispherical photographs.*

around the sampling locations. Upward-viewing photographs were captured when the maize crops were about 1 m tall. The upward-viewing pictures were captured in such a way that the leaves of both crops on the intercropped fields were included in each view. Figure 2 is the output of CAN-EYE computation of LAI in both upward- and downward-viewing cameras.

Satellite Data

The PlanetScope constellation of satellites currently has about 180+ CubeSats (4-kg satellites), with images having four spectral bands—blue (455–515 nm), green (500–590 nm), red (590–670 nm), and near-infrared (NIR; 780–860 nm)—with 3-m spatial resolution. Level-3B surface reflectance products that have been atmospherically corrected by Planet Labs using the 6S radiative transfer model and ancillary data from MODIS (Planet Labs Inc. 2020) were used. A total of four images (Table 1)—two images for each study site—were used to match the period of field data collection. Image acquisition was inhibited by the dense cloud cover that is usually present over the area during the rainy season (Kpienbaareh et al. 2021). These images were stacked together to create

Table *Crops, dates of satellite images capture, planting, and harvest dates of crops*

Field no /Crop type	Image capture date	Planting date	Harvest date
1. Maize and pigeon pea	26 December 2019 and 21 February 2020	9 December 2019	14 April 2020
2. Maize and beans	26 December 2019 and 21 February 2020	9 December 2019	14 April 2020
3. Maize and pigeon pea	4 January 2020 and 4 February 2020	3 December 2019	16 April 2020
4. Maize and beans	4 January 2020 and 4 February 2020	3 December 2019	16 April 2020

Table 2 *Description of vegetation indexes*

Vegetation index	Equation	Reference	Remarks
Normalized Difference Vegetation Index NDVI)	$\frac{NIR \ - \ red}{NIR \ +red}$	Rouse et al. 1974)	Enhances the contrast between soil and vegetation
Difference Vegetation Index DVI)	$NIR - red$	Tucker 1979)	Sensitive to the amount of vegetation; distinguishes between soil and vegetation
Enhanced Vegetation Index EVI)	$2.5*\frac{NIR-red}{1+NIR+6red \ - \ 7\ 5blue}$	Huete et al. 1997)	Uses the blue reflectance region to correct for soil background signals and to reduce atmospheric influences, including aerosol scattering
Soil Adjusted Vegetation Index SAVI)	$\frac{(1+\ )(NIR-red)}{(NIR+red+\ )}$	Huete 1988)	Corrects for the influence of soil brightness when the vegetative cover is low
Green Normalized Vegetation Index GNDVI)	$\frac{(NIR-green)}{(NIR+green)}$	Gitelson, Kaufman, and Merzlyak 1996)	More sensitive to chlorophyll concentration than NDVI
Modified Soil Adjusted Vegetation Index 2 MSAVI2)	$\frac{2\times nir+1 \ - \ \overline{(2nir+1)^2 \ - \ 8\times(nir-red)}}{2}$	Qi et al. 1994)	Mainly applied in plant growth analysis; unlike the SAVI, it does not rely on a soil correction line
Transformed Normalized Difference Vegetation Index TNDVI)	$\sqrt{\left.\frac{nir \ - \ red}{nir \ + \ red}\right] + 0\ 5}$	Senseman, Bagley, and Tweddale 1996)	Presents a better correlation between the amount of green biomass that is found in a pixel
Weighted Difference Vegetation Index WNDVI)	$nir \ - \quad \times red$	Gitelson 2004)	Very sensitive to variations in the atmosphere; has a correction factor on the slope of the soil line
Ratio Vegetation Index RVI)	$\frac{nir}{red}$	Pearson and Miller 1972)	Very correlated with leaf area index and leaf biomass; sensitive to green vegetation

Note: L = canopy background adjustment factor that addresses nonlinear, differential noninfrared and red radiant transfer through a canopy. $L = 0.5$ in this case because the canopy cover of maize averaged over the growing season is dense.

multiband images for each location using the collocation tool in the Sentinel Application Platform (SNAP) version 7.0 (ESA 2018). The final multiband images were used for computing VIs.

Data Analysis

The DHPs were processed using the CAN-EYE software (Weiss and Baret 2017) to derive in situ LAIs. Processing of the images was limited to view zenith angles smaller than 57.5° to minimize the number of mixed pixels (Mougin et al. 2014). The default values proposed by CAN-EYE for the zenith (2.5°) and azimuthal (5°) angle resolutions were maintained for the analysis. Precedence has shown the gap fraction at 57.5° zenith angle $P_0(57.5°)$ to be independent of the leaf inclination distribution function (Welles and Norman 1991) and to be capable of providing a good indirect estimate for LAI. CAN-EYE estimates LAI based on the measures of the gap fraction—the transmission of light through the canopy considering the vegetation elements as opaque (Jonckheere et al. 2005). The software uses a lookup table to provide an estimation of LAI from the gap fraction, assuming a random distribution of phyto-elements within the canopy that is without clumping (Weiss et al. 2004). The software allows for the computation of an effective (LAI_{eff}) from the gap fraction estimated from hemispherical photographs by averaging the gap fraction across azimuth and photographs for each zenithal ring. The true LAI is derived from the LAI_{eff} using the following expression:

$$LAI_{eff} \ = \ {}_0 LAI \tag{1}$$

where $_0$ is the aggregation or dispersion parameter (Nilson 1971) or clumping index (Chen and Black 1992).

Extraction of Vegetation Indexes and Prediction of LAI

We selected nine VIs that are often used as proxies for vegetation dynamics or green LAI (Viña et al. 2011; Gitelson et al. 2015; Kimm et al. 2020) to establish the relationship between LAIs and VIs (Table 2). We also used a correlation analysis to remove variables that are highly correlated to reduce the potential for compounding variables. VI values in the 5-m square areas within which the DHPs

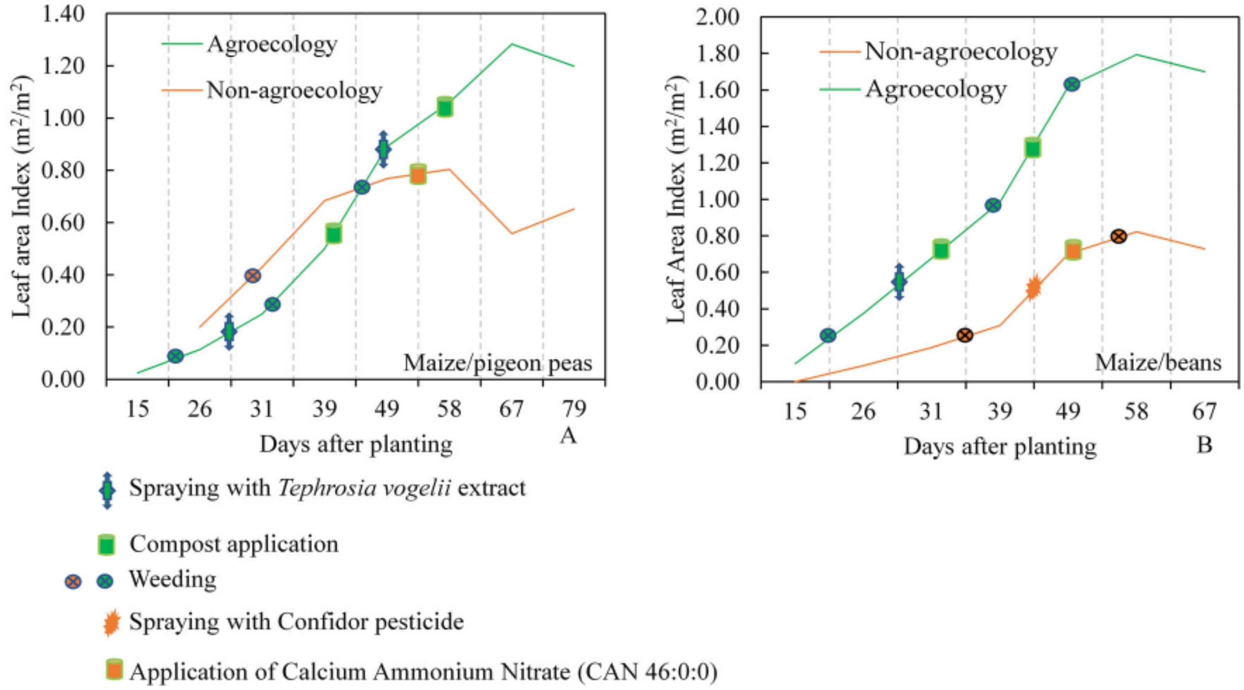

Figure 3 *Temporal trends of in-situ leaf area index LAI) during the growing season for A) maize and pigeon pea intercrop on Fields 1 and 3, and B) maize and beans on Fields 2 and 4 for agroecology green features) and non-agroecology orange features) farms. Annotations represent data collected on farm management practices and cultural practices during field visits.*

were captured were summarized for each sampling location.

A random forest (RF) regression (Breiman 2001) was used for analyzing the relationships. RF is a machine learning method that ensures good performance with several or even a single variable if the input variable is highly important and representative and the sample size is small (Tillack et al. 2014; Liang et al. 2016) and is very useful for modeling nonlinear relationships, making it appropriate for our data. RF assumes that different individual predictors predict incorrectly in different areas, resulting in an overall incorrect prediction. This incorrectness is improved when the prediction results of individual predictors are combined. To identify the most important VIs for predicting LAIs, two RF models were fitted—one with all nine VIs (RF All model) and the other with the five most influential predictors of LAIs (RF Inf model) using the varImpPlot() function in the R statistical package, as has been done in previous studies (Lee, Wang, and Leblon 2020).

The models were compared using the coefficient of determination (R^2) and the predicted values of the models were compared using the root mean square error (RMSE) metric. The R^2 is the proportion of the variance in the dependent variable that is predictable from the predictor variable. RMSE characterizes the mean differences between measured and estimated variables (Willmott 1982). Mathematically, higher R^2 and smaller RMSE represent better model accuracy (Peduzzi et al. 2012; Yue et al. 2018).

The best fit model of the two RF models was used to create a LAI prediction map for each of the individual images that were combined into the multiband images for the analysis. Using the individual images enabled us to identify the most suitable time of growth for predicting the impact of farm management practices on crop health. The writeRaster() function was used to generate the prediction maps in .tif format. The final maps were visualized, and cartographic elements were added. The predicted LAI values were extracted from the sampling points using the Zonal Statistics tool. The results were compared with the in-situ LAI and the RMSE values computed.

Results

Temporal Trends of LAI for Agroecology and Non-Agroecology Farms

Figure 3 shows the temporal trends of in-situ LAI for all the sampling locations. The results reveal a steady increase, a peak, and a decline in the LAI values in all fields. The LAIs in the AE farms, however, increased more rapidly and higher than those on the non-AE farms, even though crops on the AE farms were planted six days later than those on the non-AE farms. The trends of LAI growth appear similar during the early stages of crop growth for the maize and pigeon pea intercrop, but the disparity increases

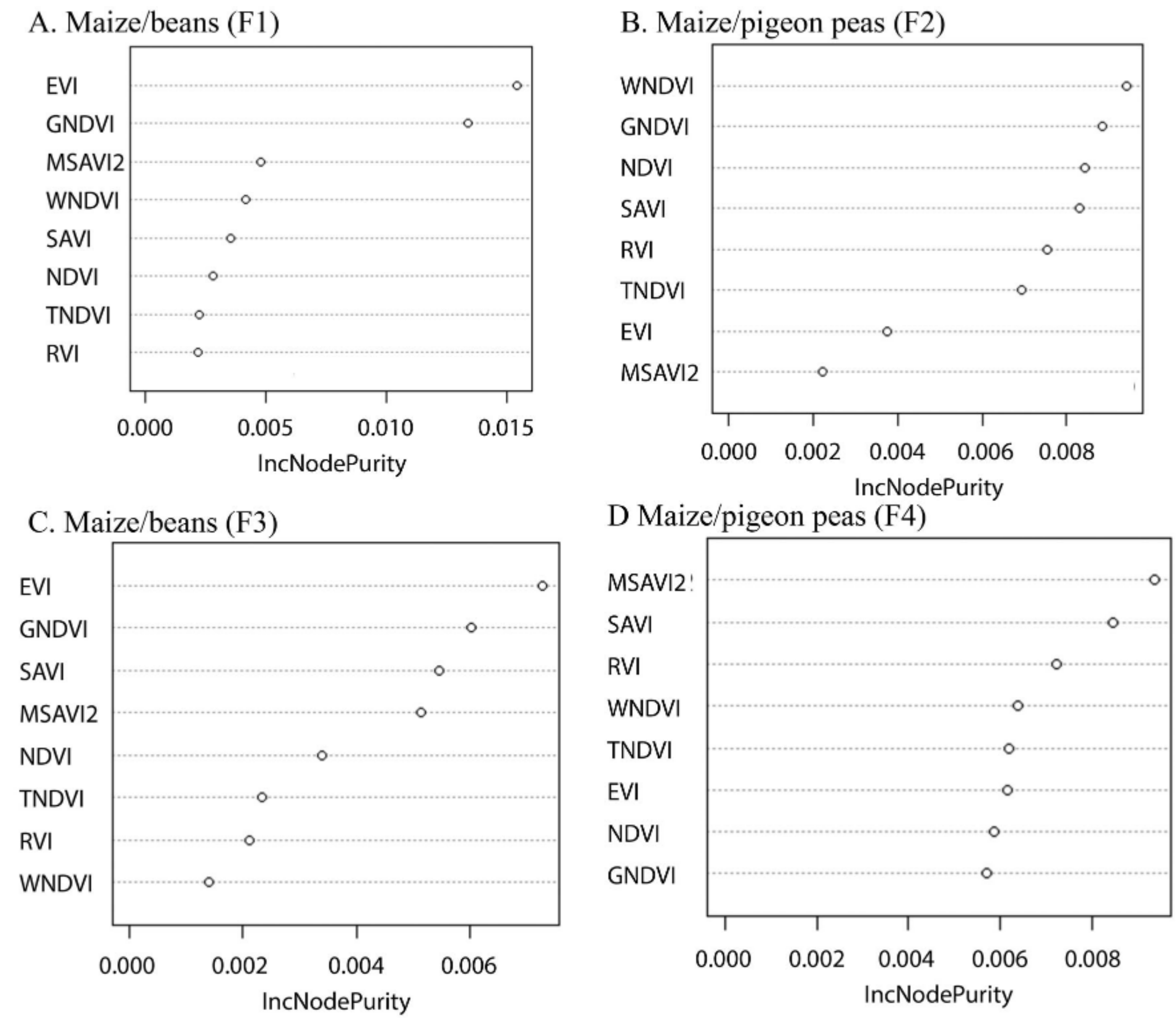

Figure 4 *Variance importance plots showing the most influential variables. A and B) Plots for the agroecology fields; C and D) plots for the non-agroecology fields. SAVI = Soil-Adjusted Vegetation Index; GNVDI = Green Normalized Difference Vegetation Index; EVI = Enhanced Vegetation Index; MSAVI2 = Modified Soil Adjusted Vegetation Index 2; WNDVI = Weighted Difference Vegetation Index; NDVI = Normalized Difference Vegetation Index; RVI= Ratio Vegetation Index; TNDVI = Transformed Normalized Difference Vegetation Index.*

sharply in the latter stages of growth, with the measurement showing continuous growth in AE farms (peaking at 1.28 m^2/m^2) and tailing off in non-AE farms after 0.80 m^2/m^2, earlier than on the AE farms. Similarly, LAIs in the maize and bean farms showed higher values for the AE farms (peaking at 1.29 m^2/m^2) than the non-AE farms (peaking at 0.97 m^2/m^2) in the same number of days after planting.

Farm-Level Management Practices and LAI Trends

The annotations in Figure 3 show the farm management practices applied on the farms. Comparing the trends of the in-situ LAI growth with the documented management practices shows a relationship between the patterns of LAI change and farm management practices. The AE farmers timely applied compost and managed weeds on their farms more frequently than their non-AE farm counterparts. Further, the compost and other soil-enhancing interventions that were applied on the AE farms were turned into the soil during weeding to ensure maximum absorption, whereas non-AE farmers applied a single dose of synthetic fertilizer in the latter stages of the crop s growth because of delays in releasing subsidized fertilizers and inaccessibility due to high cost, despite the subsidies. On the AE farms, insect, pest, and disease infestations were treated using extracts of *Tephrosia vogelii*, *Tithonia diversifiolia*, and *Vernonia amygdalina* at different stages of the growing season. We observed that these botanical pesticides were effective for treating blister beetle infestations. The non-AE farmers, however, relied on agrochemicals to treat insect infestation. The first author realized on one of the visits that the farmers at Field 3 (non-AE) used Confidor 200 SL pesticide

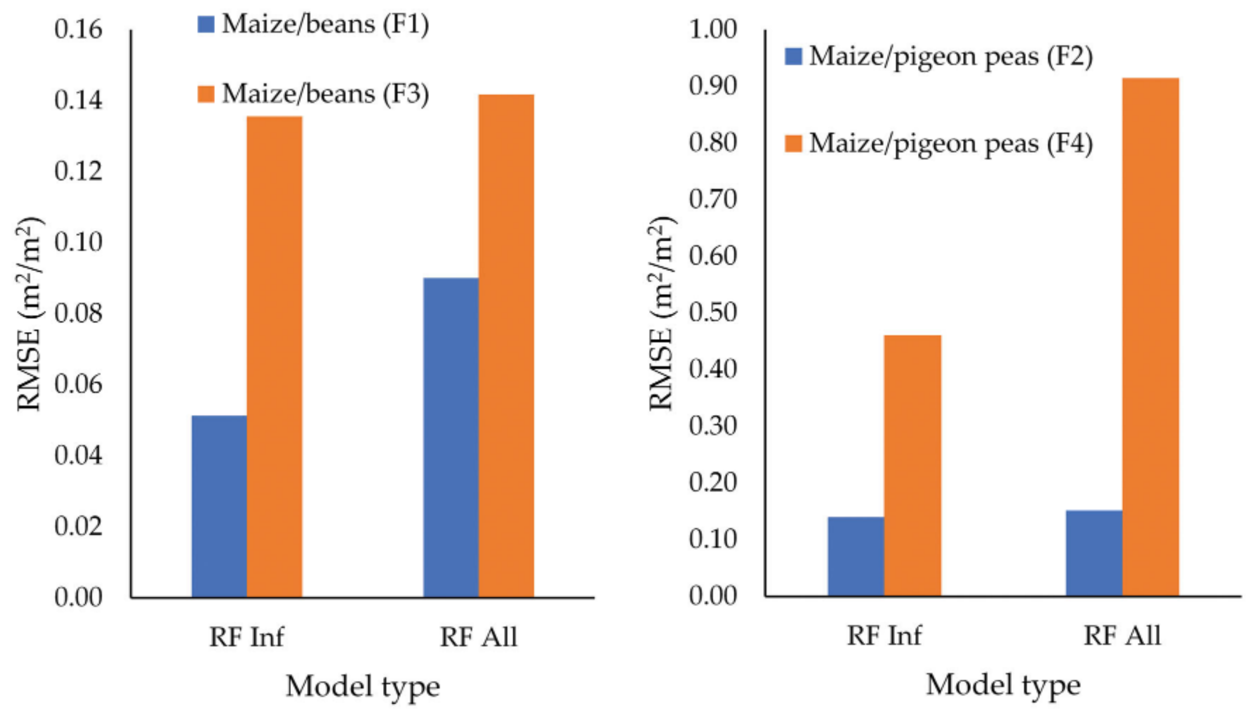

Figure 5 *Root mean square error RMSE) of random forest RF) model with the five most influential variables RF Inf) and RF model with all the variables RF All). F1, F2, F3, and F4 are Fields 1 through 4, respectively.*

thatt was expired to attempt to destroy blister beetle infestation on the maize and beans farm.

Relationships Between in-Situ LAI and Vegetation Indexes

Figure 4 shows the variance importance plots that identify the most influential variables for predicting LAI. Soil-Adjusted Vegetation Index (SAVI) emerged as an influential predictor in all four fields. Except for Field 4, Green Normalized Difference Vegetation Index (GNDVI) was also influential in predicting LAI in all the other fields. Figure 5 compares the RMSE metrics and Table 4 shows the R^2 values of the RF Inf and RF All analysis. The RMSE for the RF Inf was lower for Field 1 (AE) than Field 3 (non-AE) but the results were similar for the RF All models for all farms. For the maize and pigeon peas farms, Field 2 (AE) produced the lowest RMSE values for both RF Inf and RF All compared with Field 4 (non-AE) but overall, the RF Inf outperformed the RF All. The results also show that the results for both Fields 3 and 4 were not statistically significant (< 0.05) in both models (Table 3). Further, we found that the R^2 statistics for Fields 1 and 2 were higher and statistically significant compared with the non-AE farms (Table 3). These revelations suggest that data for the non-AE farms cannot be used for monitoring farm management practices applied on a farm and cannot be applied for crop health monitoring because the usual management practices likely negatively affected the biophysical characteristics of the crops. As a result, only data from the AE farms were used for the validation analysis.

Table 4 shows the validation results for the models. Contrary to the expectation that a model with more variables might be more robust, the RF All model attenuated, implying the less influential predictors among the nine variables exerted a negative influence. The RF Inf models, however, remained robust at the 95 percent confidence level. The RMSE values for the RF Inf model also were reduced compared with the values in Figure 5, suggesting that the LAI for maize and beans and maize and pigeon peas can be more accurately predicted using selected VIs.

Prospective Monitoring of Crop Health to Assess the Impacts of Agroecology

The RF Inf models for Fields 1 and 2 were used to generate prediction maps for different dates after planting. The predicted values were extracted for each of the sampling locations. When compared with the in-situ LAIs, Table 5 shows that the RF Inf models accurately predicted the LAIs in the latter stages of the growing season (21 February 2020) than during the earlier stages of the season (26 December 2019). The correlation coefficients were strong and statistically significant at the 95 percent confidence level ($r = 0.92$ and $r = 0.84$ for Fields 1 and 2, respectively) on 21 February 2020 (seventy-five days after planting). The correlation coefficients were, however, weak ($r = 0.23$ and $r = 0.21$ for

Table 3 *Statistics for the calibration of the leaf area index model using random forest regressions*

Management regimes	Variables	Model	R^2	*p* value
Agroecology	Maize and beans Field 1)			
	EVI, GNDVI, MSAVI2, WNDVI, SAVI	RF Inf	0.74	0.02*
	All indexes	RF All	0.52	0.18
	Maize and pigeon peas Field 2)			
	WNDVI, GNDVI, NDVI, SAVI, RVI	RF Inf	0.82	< 0.001*
	All indexes	RF All	0.72	0.04*
Non-agroecology	Maize and beans Field 3)			
	EVI, GNDVI, SAVI, MSAVI2, NDVI	RF Inf	0.27	0.32
	All indexes	RF All	0.19	0.08
	Maize and pigeon peas Field 4)			
	MSAVI2, SAVI, RVI, WNDVI, TNDVI	RF Inf	0.21	0.89
	All indexes	RF All	0.65	0.07

Note: EVI = Enhanced Vegetation Index; GNDVI = Green Normalized Vegetation Index; MSAVI2 = Modified Soil Adjusted Vegetation Index 2 MSAVI2); WNDVI = Weighted Difference Vegetation Index; SAVI = Soil Adjusted Vegetation Index; NDVI = Normalized Difference Vegetation Index; RVI = Ratio Vegetation Index; TNDVI = Transformed Normalized Difference Vegetation Index; RF = random forest.
*Significant at < 0.05.

Table 4 *Statistics for modeling the validation data set using different approaches*

Variables	Model	RMSE	R^2	*p* value
Maize and beans Field 1)				
EVI, GNDVI, MSAVI2, WNDVI, SAVI	RF Inf	0.32	0.90	< 0.003*
Maize and pigeon pea Field 2)				
WNDVI, GNDVI, NDVI, SAVI, RVI	RF Inf	0.42	0.88	0.041*

Note: RMSE = root mean square error; EVI = Enhanced Vegetation Index; GNDVI = Green Normalized Vegetation Index; MSAVI2 = Modified Soil Adjusted Vegetation Index 2 MSAVI2); WNDVI = Weighted Difference Vegetation Index; SAVI = Soil Adjusted Vegetation Index; NDVI = Normalized Difference Vegetation Index; RVI = Ratio Vegetation Index; RF = random forest.
*Significant at < 0.05.

Table 5 *Correlation coefficients and root mean square error RMSE) of the random forest - based prediction model when applied to the individual PlanetScope images used for the analysis*

	26 December 2019		21 February 2020	
Field no	Correlation coefficient	RMSE	Correlation coefficient	RMSE
Field 1	0.23	0.77	0.92	0.14
Field 2	0.21	0.80	0.84	0.23

Fields 1 and 2, respectively) and insignificant at the 95 percent confidence level for the 26 December 2019 date (eighteen days after planting). The RMSE values from comparing the in-situ and predicted LAI further confirmed that the model predictions of LAI for the latter stage of the growing image are more accurate (RMSE $= 0.14\,m^2/m^2$) than the earlier growing season image (RMSE $= 0.23\,m^2/m^2$).

Figure 6 shows the distribution of predicted LAI based on the RF Inf models for the two AE farms. The green color represents high LAI values (or healthier crops) and red represents low values. The low LAI patch within Figure 6B coincides with a drainage way on the field where crops were damaged by a flood resulting from a rainstorm two days before the image was captured. The deep red in Figure 6C coincides with a termite mound where crops were not yet planted when the images were captured. Overall, the estimated values for the 21 February image showed more agreement with in-situ data than that of the 26 December image.

In summary, the study results reveal that applying agroecological methods on a farm could potentially improve crop growth in smallholder farming systems in Malawi. We also observed that farms on which AE is practiced produce statistically significant results (Tables 3, 4, and 5) when LAIs were predicted for future crop monitoring, suggesting that healthier AE crops tend to produce better biophysical parameters that can be captured by satellite sensors and that remote sensing can be used to assess management practices on the agricultural landscape.

Discussion

Overall, the results from this study show that agroecological management can contribute to crop growth and health if management practices are applied during critical crop growth stages. These findings are consistent with previous studies (Viña

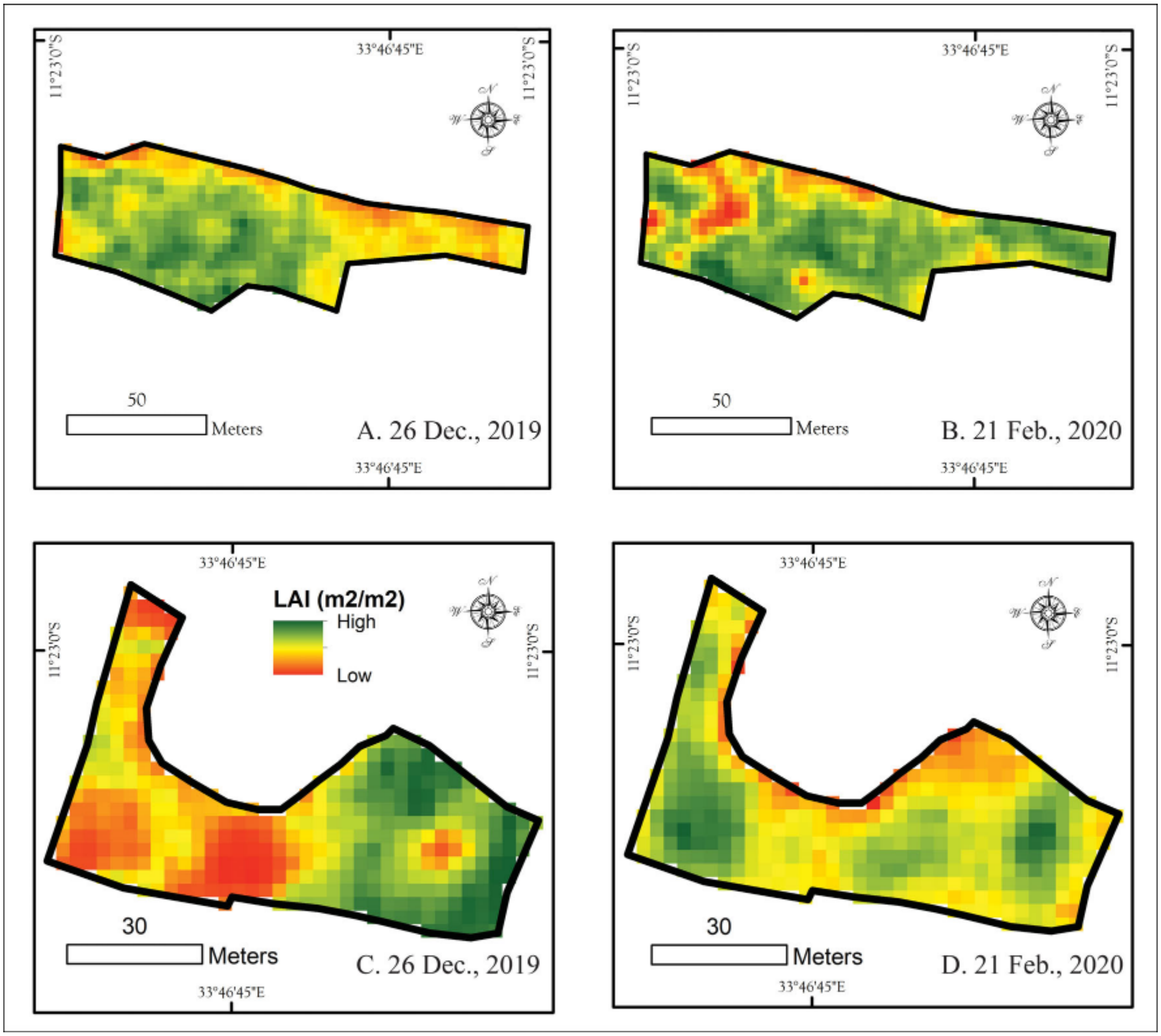

Figure 6 *Leaf area index prediction map for maize and beans intercrop derived from the random forest regression with the five most influential variables. Images used were from A and B) 26 December 2019, and C and D) 21 February 2020, for Fields 1 and 2.*

et al. 2011; Kross et al. 2015) that examined the impacts of agronomic practices on crop health and productivity in other contexts. For instance, Ayyobi, Olfati, and Peyvast (2014) found that composting positively affects soil structure and nutrient availability, which can help increase fertility without negative effects on human health and the environment. According to Wezel et al. (2014), implementing effective farm management practices such as stringent weed control and timely application of soil-enhancing materials such as manure and biofertilizers are key to successful crop growth in agroecological farming systems. These reasons likely explain why the farms managed with AE produced healthier crops compared to the non-AE farms. The principles of AE emphasize the efficient use of resources such as nitrogen, atmospheric carbon, and solar radiation to improve crop yield (Wezel et al. 2020), which explains the improved health of crops on the AE farms. These findings prove that participatory AE plays a significant role in the sharing of information for improving farming practices that are in line with the social movement dimension of AE. For instance, timeliness in the application of interventions on the AE farms was mainly due to the lessons learned from interactions with other farmers in the networks of the farmers over the years and during the season (Kansanga et al. 2020). The non-AE farmers did not have any of this social capital to rely on for critical farming information. Therefore, food system transformation in these smallholder farming systems can be achieved through participatory AE.

The RF Inf regression with the most influential variables more accurately predicted LAIs with relatively higher R^2 and lower RMSE values compared to RF All (see Table 4). Consistently, previous studies by Kross et al. (2015) predicted LAI in mixed corn and soybean farms in eastern Ontario, Canada and achieved an R^2 of 0.85, and Zhao et al. (2019) found that RF regression models are more accurate than linear regression models because they can model complex, nonlinear, small-sample data sets (Cooner, Shao, and Campbell 2016). Together, the Enhanced Vegetation Index, GNDVI, Modified Soil Adjusted Vegetation Index 2, Weighted Difference Vegetation Index, and SAVI emerged as the most important predictors of LAI for the maize and bean crop whereas the WNDVI, GNDVI, Normalized Difference Vegetation Index, SAVI, and Ratio Vegetation Index were the total sum of the most important predictors of LAI for maize and pigeon pea farms. The observation is consistent with previous studies (Srinet, Nandy, and Patel 2019; Peter et al. 2020) that identified these indexes as important predictors of LAIs of maize, beans, and pigeon peas. Peter et al. (2020), in a similar study in Malawi, also found that multivariable regression equations were more useful for predicting crop health even though they used UAV images with relatively higher spatial resolution (14–27 cm). Further, evidence (de Sousa et al. 2020; Mart´n-Ortega, Garc´a-Montero, and Sibelet 2020) suggests that vegetation indexes are influenced by several factors, including climate, soil type, soil nutrient content, and reflectance of the crops (de Sousa et al. 2020; Mart´n-Ortega, Garc´a-Montero, and Sibelet 2020). The evidence from these previous studies likely explains why some of the VIs emerged as more important predictors than others. Future studies should incorporate climate and soil variables in the analysis to ascertain their effects on predicting LAI in such smallholder contexts.

Consistent with several other studies (Baez-Gonzalez et al. 2005; Ban et al. 2016) that examined LAI prediction for crop health monitoring, we found that on both AE farms, the predicted LAI values were statistically significantly correlated with the in-situ LAI values and had lower RMSE values (see Table 5) during the latter stages of the growing season (sixty days after planting) compared with the earlier stages of crop growth. This observation is likely because of the use of seasonal averages of in-situ LAI for the analysis. During the earlier stages of the season, not much was accomplished in terms of the agroecological practices applied on the farms. At the latter stages of the season, however, the farms had been treated with several agroecological methods, hence the crop biophysical parameters reflected the impact of these treatments. This finding implies that to derive the full benefits of agroecological practices, there has to be consistency and persistence in the application of farm interventions such as compost application, weed control, and manure application. The finding also suggests that to accurately predict the seasonal health of crops in such small farms using satellite data, it is important to target stages of the growing season when crop biophysical parameters are reflective of the management practices applied on the farm. Prospectively predicting the LAI using unitemporal satellite data has policy relevance for local agricultural extension officers and smallholder farmers.

Although the study provides useful information on the significance of agroecological management and the combination of these practices for improving crop health, a limitation of the approach used is that a unitemporal perspective on the impact of AE is presented from the geospatial approach. Although this approach provides useful information on the significance of agroecological management practices in smallholder contexts, there is a need for more information on how other farm conditions (e.g., soil structure) and environmental factors (e.g., weather, including rainfall amount, dry spells, etc.) might have contributed to determining crop health in the two instances. Future studies should conduct soil analysis to establish the actual differences in soil fertility resulting from the different agronomic practices. Additionally, a longitudinal analysis would be useful for isolating any possible external factors, other than agronomic practices that might affect crop health. Finally, using drones equipped with high-resolution multispectral bands with many channels will improve the selection of indexes for understanding crop health in the area.

Conclusions

In the context of climate change, increasing global food insecurity, and rapid land degradation, AE is an important approach through which yields can be improved while ensuring the ecological integrity of the environment. In this study, we used a geospatial approach to assess the impact of a combination of agroecological practices on crop health and to prospectively determine the seasonal impacts of AE on crop health using satellite-derived VIs and an RF machine learning regression analysis. The results suggest that adopting a comprehensive farming approach that involves a blend of agroecological practices and integrates sustainable soil management practices can produce healthy crops that could potentially increase yield. The geospatial method applied in this study demonstrates that similar to field experiments, geospatial techniques present a cost-effective approach to large-scale assessment of the impact of AE on crop health. Future studies should apply multiseason data and more sample farms for a longitudinal study to understand the spatial and temporal dynamics in the distribution of LAIs to better understand the dynamics of agroecological farm management practices.

This study makes valuable contributions toward the conceptualization of crop health in the field of pest, disease, or weed management, by promoting a transdisciplinary understanding of crop health holistically in agroecology (Vega et al. 2020; Wezel et al. 2020) through a geospatial perspective. By using a geospatial approach, we also make an empirical contribution to the evolutionary trends in understanding AE as a way of transforming smallholder agricultural production through a combination of practices that are integrated with indigenous farming knowledge. Kpienbaareh et al. (2020) demonstrated how participatory AE can lead to the amplification of agroecological knowledge to enhance ecosystem services and biodiversity conservation, an observation that falls within the growing trend of geospatial applications for exploring the impacts of AE. As climate change and food insecurity continue to dominate the public policy sphere, AE is gaining increasing importance as a sustainable alternative to adaptation. Geospatial analysis can play an important role in improving our understanding of agroecological management processes, therefore aiding in the increasing push to transition to sustainable food systems.

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Note

[1] In the study context, a village area is used to describe a large area with smaller villages usually of farming households.

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