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Climate Trends, Hydrologic Modeling, and Land Use Analysis in Malawi

A Report by the Megatrend One Biophysical Science Team

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EXECUTIVE SUMMARY

This report is a summary of recent efforts to look at the physical and biophysical aspects of historical and projected climate, water, and land use change in Malawi. For improved projections of climate, water, and land use, our work has centered on modeling. We are using various models for a variety of tasks, but the main objective has been to calibrate these models with the best available data for producing projections that are more accurate. The next step is to integrate these models via coupled processes at appropriate length and time scales and assess their reliability for making useful projections. Our ultimate focus is to develop a more consistent methodology for predicting climate impacts on water, agriculture, and land use that operates across scales, i.e., trends that vary across time and space at different resolutions. This methodology should be consistent in that the temporal and spatial scales of biophysical projections will be useable at scales needed and will be transportable to other regions. This work was completed mainly through a combination of geographic information system (GIS), statistics, and process-based models with an aim to better assess agricultural changes and their driving factors.

Two trips to Malawi in 2013 and 2014 formed the basis of the field work in establishing contacts, setting up baseline data gathering operations, installing weather stations, sharing data, and identifying key locations for study. This work was done by Nathan Moore, Joseph Messina, Pouyan Nejadhashemi, Victoria Breeze, Umesh Adhikari, Matthew Herman, Brad Peter, and Hannah Deindorfer. The modeling and data analysis was done at MSU. In Malawi, we worked with David Mkwambisi to set up the weather stations and ensure data collection with his team.

Several new findings show clear evidence of changing patterns that influence weather, hydrology, and agricultural land use in Malawi. First, the onset of the rainy season (start of season) is delayed by approximately six days and the trend shows increasingly later start dates. The United States Agency for International Development (USAID) funded Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) datasets were found to be acceptable for use in other models, based on the close correlation of CHIRPS data with observed weather station data. For better understanding of spatial relationships between weather, climate, and food production in Malawi, five new weather stations in agricultural sites have been established and will help reduce this uncertainty. Second, watershed models have been calibrated but need further validation to capture peak flow. Watershed models have been constructed for all of Malawi's major watersheds. Third, the existing datasets on which land is in agriculture disagree significantly. This is a problem for integrating models. In addition, net primary productivity (NPP) estimates show declines in productivity over Malawi's recent history. Finally, we have shown that extensification is poorly characterized among several independent datasets. We have little understanding of what locations are marginal for agriculture and why assessments disagree.

Biophysical patterns (land use, greenness, rainfall, etc.) are poorly measured in Malawi both in spatial and temporal resolution as well as in terms of coherent and consistent indicators of land cover. Some relatively straightforward evaluations of weather data, land cover data, and crop yield across scales should be able to improve agricultural predictions of yield and nutrient stress significantly. Currently there is disagreement even in the sign of change (i.e., whether it is positive or negative). More data at finer scales is always welcome and reduces uncertainty, but ultimately significant effort is needed to describe where processes are inconsistent at different scales (e.g., they appear at fine scales but not at coarser scales, or how drought detection can depend sensitively on the selection of time scale) and how models can make useful projections in the face of disagreement between various data sources.

There are several implications of these results. Crop yields may be declining despite the Food and Agricultural Organization (FAO) estimates. New methods are being developed to better characterize the biophysical changes in recent decades. These methods can be used and improved by Malawi researchers and field teams of MSU researchers to improve predictions. Several training sessions, short courses, etc. need to be implemented to develop the scientific expertise for doing integrated modeling and assessment. Specifically, training is needed for climate statistics, hydrologic modeling, and remote sensing/GIS.

This report is arranged in three sections: (A) Climate Trends, (B) Hydrologic Modeling, and (C) Land Use Analysis.

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ACRONYMS

CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
DSSAT	Decision Support System for Agrotechnology Transfer
FAO	Food and Agricultural Organization of the United Nations
FEWSnet	Famine Early Warning Systems Network
GCM	general circulation model
GIS	geographic information system
LUANAR	Lilongwe University of Agriculture and Natural Resources
MSU	Michigan State University
NASA Power	National Aeronautics and Space Administration Prediction of Worldwide Energy Resource
NPP	Net Primary Productivity
NSE	Nash-Sutcliffe Efficiency
PBIAS	percent bias
RSR	root mean square error to the standard deviation of measured data
SALUS	Systems Approach to Land Use and Sustainability
SOS	Start-of-the-Rainy-Season
SWAT	Soil and Water Assessment Tool
USAID	United States Agency for International Development

A. CLIMATE ANALYSIS

1. INTRODUCTION

Malawi's meteorological data is sparse; only 26 stations are available and not all have sufficient data density for use in analysis. We found only 19 that passed basic quality control tests. We first analyzed these station data to detect any significant trends in seasonality, and then we compared these to gridded datasets that will be used in multiple models that require climate data as an input. In addition, we are constructing climate regime diagrams to assess how Malawi's agricultural regions are shifting over time. Thus far we have examined the new CHIRPS high-resolution gridded dataset to determine whether the onset of the rainy season has changed significantly or not since the 1960s.

2. METHODOLOGY

We used the Famine Early Warning Systems Network (FEWSnet) algorithm to calculate the start of the rainy season (SOS). The SOS algorithm is simple: If the first 10-day period (two pentads) has 25 mm of rain and the following two pentads have 20 mm of rain, then the season has started. We used an integrated Python-ArcGIS script to test the SOS for each year of available data, 1981-2013. We ran a conditional test on pentads starting in October through the end of January, to test a larger buffer around the traditional start of the rainy season in November.

The biggest task in comparing the two datasets was compressing the amount of data into ArcGIS. First, we took a map of every year of CHIRPS data, overlaid it onto a map of all of the rainfall collecting locations, and cut out the places where the CHIRPS data points were closest to the station data. Then, we took both the station data and CHIRPS data and further narrowed the data from daily to pentadal (five-day sums). In order to compare the start of season for each year in both CHIRPS and station datasets, we used an algorithm that would give a value for the cell of the first pentad in which was met the criteria of Pentad A+B >= 25mm, and Pentad C+D>= 20mm. This was used to mark the date of the start of season. In order to compare the dates for both CHIRPS data and station data over time, we plotted the start of season dates for both datasets on a graph, with each year on the X axis and date on the Y axis. The resulting lines showed an almost identical pattern, of which we were able to calculate the R-squared values, showing how well they fit one another.

We have several conclusions that have significant implications for food production in Malawi at the national level. First, the overall start of the rainy season across all Malawi has shifted later in the year by about six days from November 16-20 to November 22-26. These data also show that the rains arrive later in the south (~9 days) than the north, and later in high-elevation northern areas (~7.5 days) than low-elevation northern areas (~3.5 days) (see Figure 1).

We also developed a new indicator called Early SOS that refers to the first SOS data among any of Malawi's 28 districts. This Early SOS has shifted dramatically later—approximately 24 days, from early October to the beginning of November. The shift in Early SOS is most pronounced in the south (~16 days), but also noticeably in the low-elevation northern area (~9 days). The high-elevation northern area showed a slight shift earlier in the year by ~3 days. This curious spatial variation in SOS contraction is not well understood.

2.1. Selected Agricultural Areas: Mzimba, Karonga, and Thyolo

We investigated the change in SOS across three districts of Malawi: the high-elevation northern district of Mzimba, the low-lying northern district of Karonga, and the southern district of Thyolo (See Figures 1, 2, and 3).

The SOS in Mzimba shifted from mid to late November, Karonga from late November to early December, and Thyolo from early November to mid November.

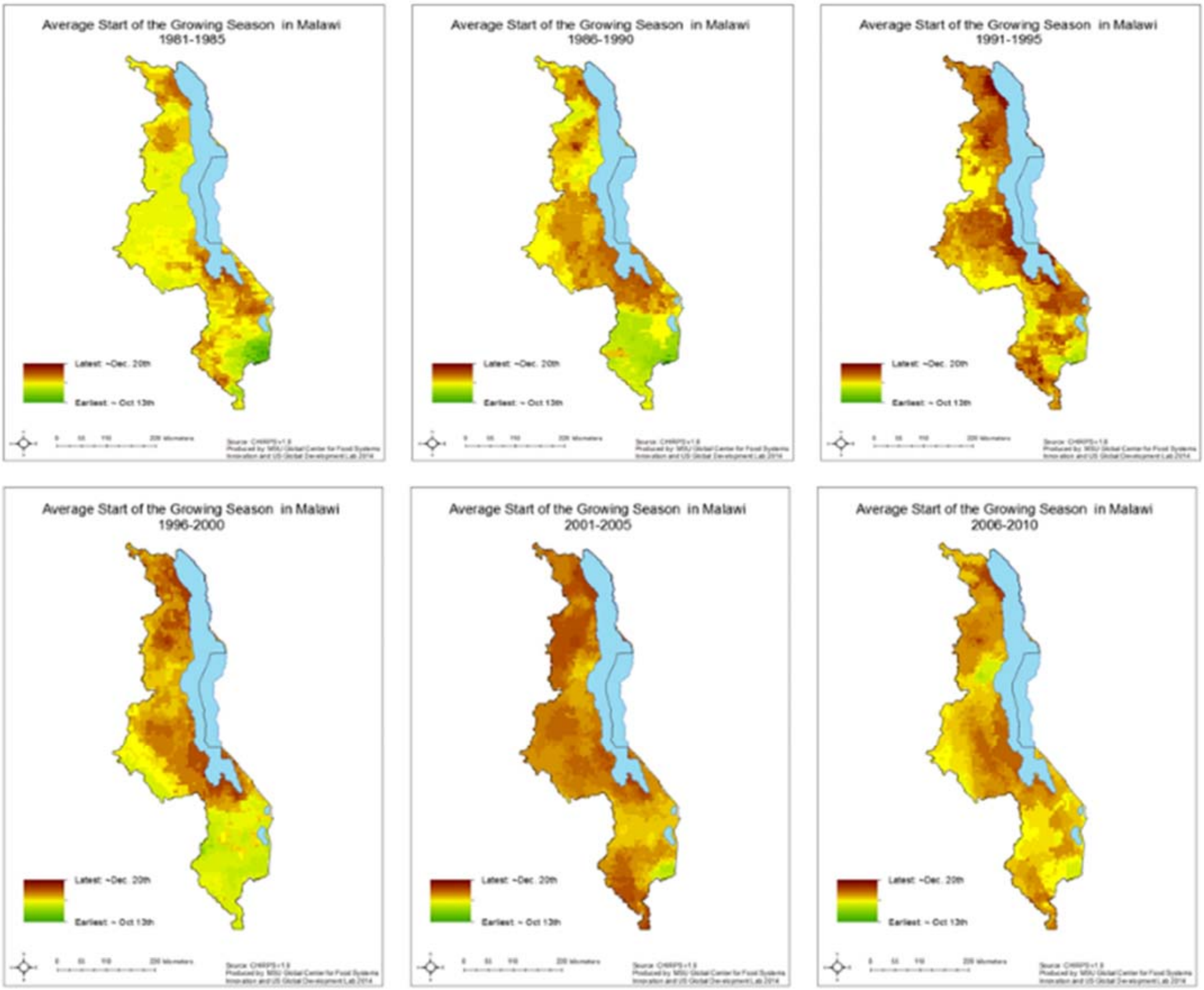
Mzimba: The mean SOS shifted by approximately 1.5 pentads or 7.5 days. The minimum SOS actually shifted forward by three days. Maximum SOS shifted back nine days and the range in SOS contracted by 12 days.

Karonga: The mean SOS shifted by approximately 0.7 pentads, or 3.6 days. The minimum SOS shifted back by nine days, maximum by five days, and range in SOS increased by four days.

Thyolo: The mean SOS shifted by approximately 1.9 pentads or 9.4 days. The minimum SOS shifted back by 16 days, maximum by 12 days, and the range in SOS increased by four days. This is the earliest district.

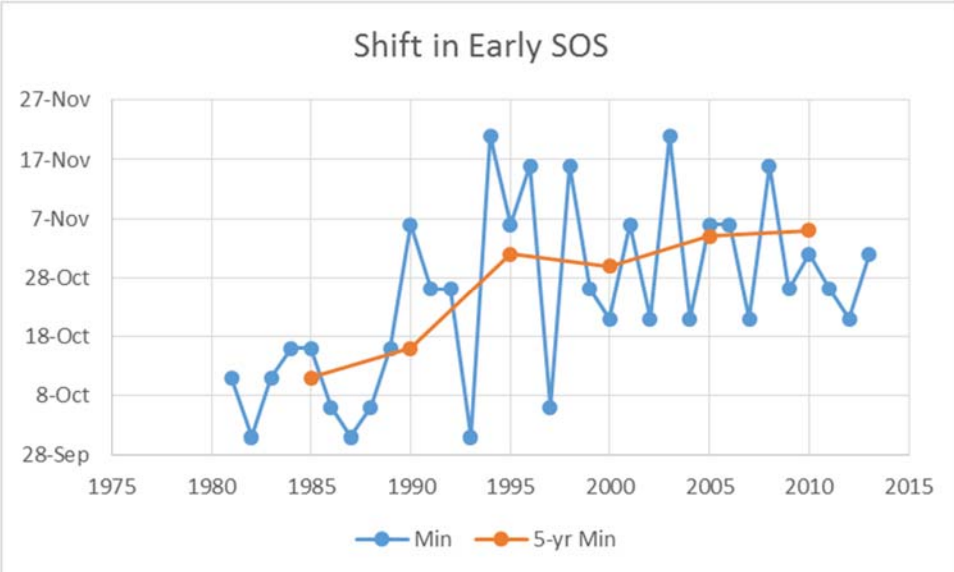
Figure 1. Progressive SOS Maps in Five-Year Intervals. Brown=Late Onset (Dec.), Green=Early Onset (Oct.)

Shift in Five-Year Average Mean SOS (1981-2010)



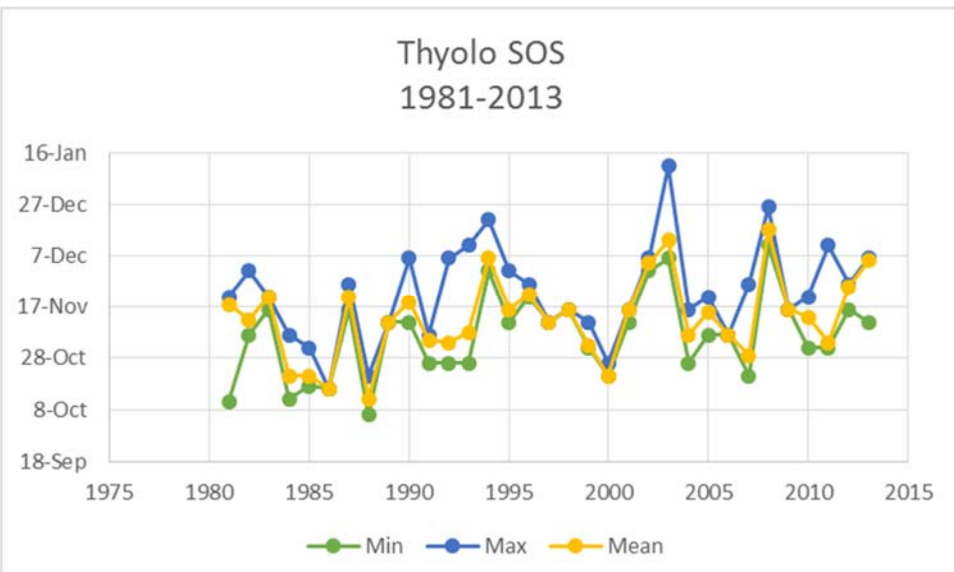
Source: Author's calculations with data from CHIRPS 1.8.
Note: Larger versions of these maps avaliable on request.

Figure 2. Earliest SOS for Any District in Malawi over the Observed Period



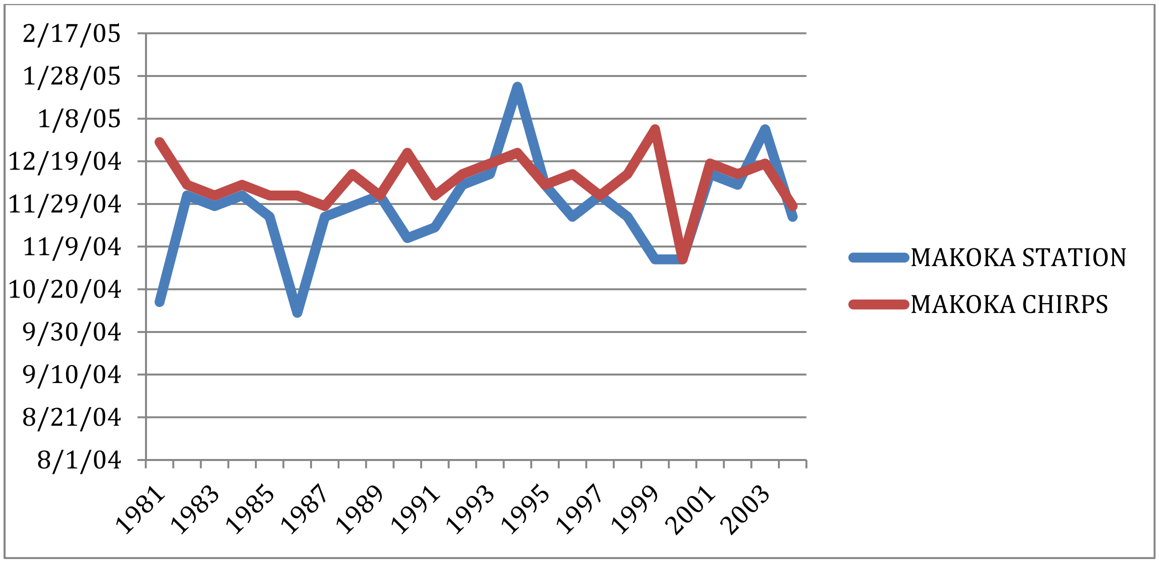
Source: Author's calculations with data from CHIRPS 1.8.

Figure 3. Example SOS Trends for All Pixels in Thyolo District



Source: Author's calculations with data from CHIRPS 1.8.
Note: Minimun and maximum represent extreme outlier observations from the gridded dataset for locations within Thyolo district.

Figure 4. CHIRPS and Station SOS Time Series for Makoka, Malawi



Source: Author's calculations with data from CHIRPS 1.8 and Malawi Met. Office weather stations.

Gridded data are excellent for use in models of food production and related processes, but gridded data often fail to capture properly the heterogeneity of station data. Unfortunately, Malawi's network of weather stations is not sufficiently dense to provide a reliable representation of climate throughout the country. As part of validating the use of gridded data, we correlated the gridded pixels coinciding with the station locations.

Correlations between CHIRPS and station data (Table 1) are fairly good on average. A few stations (Makoka, Chitedze) are low but still show some trend agreement (Figure 4). We need to test other gridded datasets to calculate which best fit Malawi data and thus which are best for use in the Systems Approach to Land Use and Sustainability (SALUS) and the Soil and Water Assessment Tool (SWAT). Surprisingly, none of the gridded datasets thus far come out as clearly superior with respect to frequency, spatial resolution, bias, and interquartile range.

Table 1. SOS Data Correlations between CHIRPS 1.8 and Station Data

0.728	Chitipa	0.493	Salima
0.700	Karonga	0.891	Nkhotakota
0.768	Bolero	0.573	Dedza
0.422	Mzimba	0.170	Makoka
0.578	Mzuzu	0.599	Chileka
0.454	Nkhata Bay	0.625	Chichiri
0.517	Kasungu	0.670	Bvumbwe
0.499	Lilongwe	0.688	Mimosa
0.306	Chitedze	0.800	Thyolo
		0.646	Ngabu

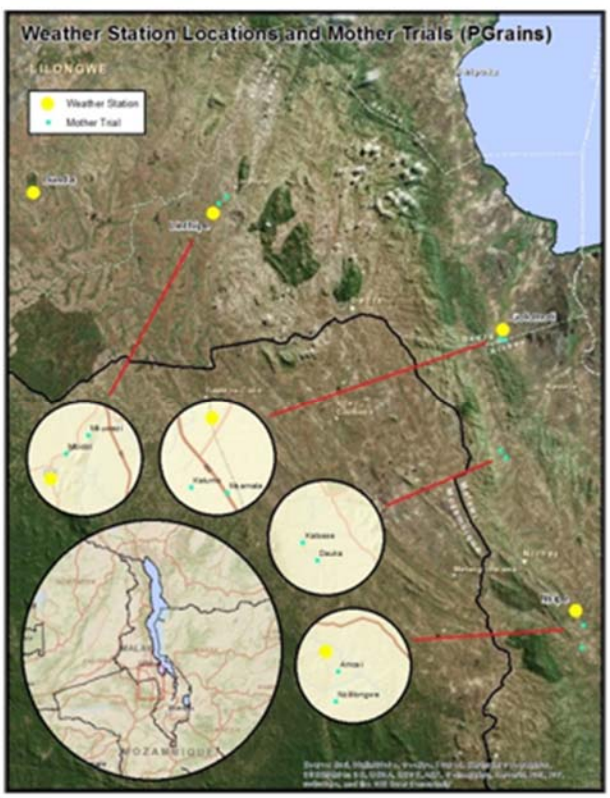
Source: Author's calculations from SOS and CHIPS data.

While CHIRPS has a favorable spatial and temporal resolution, National Aeronautics and Space Administration Prediction of Worldwide Energy Resource (NASA Power) has better performance metrics. We will need to test multiple datsets for uncertainty propagation and sensitivity to be able to report reliability to end users.

2.2. Weather Station Construction in Malawi

Four weather stations have been installed at Bunda College, Linthipe, Golomoti, and Nsipe. In addition to construction and installation, training on data collection and station operation was provided for technical staff and faculty at Bunda College (Figure 5). With the four weather stations built, we now have access to the following data at those sites: wind speed, wind direction, barometric pressure, temperature, relative humidity, dew point, precipitation, photosynthetically active radiation (PAR), and soil moisture. Having these data collected in critical, representative transitional areas for agriculture will allow us to measure how well traditional gridded datasets perform, how much improvement can be obtained by building new infrastructure and scientific capacity, and—most critically—how changes in land use and agricultural activity are coupled to shifts in weather and climate. If marginal land use increases or if deforestation continues along the agricultural periphery, gridded datasets interpolating at larger scales will fail to capture this feedback. These fine-scale interactions are crucial for identifying key processes in agricultural change and we need stations placed appropriately to measure them.

Figure 5. New Weather Station Locations



Source: Author's GPS data with imagery from NASA MODIS.

3. NEXT STEPS AND FOLLOW-UP

First, we need to test whether the end of the rainy season has arrived earlier, and map the spatial pattern of rainy season duration and any changes. This is crucial to understanding physical drivers of land change variability. In addtion, we need to perform a cluster analysis on the curious spatial variation in SOS contraction across Malawi, and assess whether or not the patterns are consistent with local, regional, or synoptic patterns of weather forcing. Part of this can be done by looking at coarse versus fine scale datasets, and so we will test the FEWSnet algorithm on several other datasets to identify scales of pattern similarity. The new weather stations will help here; we plan to assess the utility of the new weather stations and determine the need for expansion in part due to locations where trends disagree across datasets. In cases where the rainfall patterns are poorly characterized by the FEWSnet algorithm, we may need to create alternate algorithms that are more appropriate for agriculture (1/e, etc.). This will further aid in testing to see whether the climate trends are clustered or not.

The main objective for identifying the best gridded dataset is to get a good handle on estimating its accuracy in addition to identifying products most appropriate for processes at multiple scales (watershed, point, and national) so that we have a cohesive methodology (consistent timescales, limited error propagation) for examining climate impacts on agriculture. Once the integrated methodology is tested and validated, we can test this new tool for assessing vulnerability in Cambodia and other regions.

Currently we have no dataset that is both spatially and temporally high-resolution with low error. State-of-the-art modeling now requires daily high-resolution gridded data and current datasets fall short in accuracy. Ultimately we need to develop such a high-resolution dataset—something like a CHIRPS/NASAPower hybrid—for use in crop productivity and farming analysis as well as for error propagation studies. Then we will need to assess bias in the historical general circulation model (GCM) simulations that we have already acquired. The historical simulations will be used to constrain the accurcy of our rainy season predictions. From this we will be able to calculate the bias for the future projections and bias-correct them for use in other elements of Megatrend One (e.g., the crop models and SWAT). Understanding how delays or changes in the rainy season propagate into other systems is crucial to aid planning for farmers and other food systems stakeholders.

B. HYDROLOGIC MODELING

1. SUMMARY

SWAT is a watershed model developed to quantify the impact of land management practices in large, complex watersheds. In this study, SWAT was used to assess the impact of climate change on land and water resources in Malawi. By comparing baseline conditions with the projected conditions, the impact of climate change on crop-production-related water balance components—such as actual evapotranspiration, soil water content, water percolation, surface runoff, base flow—and water yield will be assessed. Calibration and validation of a SWAT model was completed for all the watersheds (eight in total), for which observed data were available. These models were then run for 20 years (1981-2000) to serve as a base period for the impact assessment. Five GCMs, which have been reported to reproduce the mean annual precipitation cycle in Eastern Africa, were downscaled for the mid-21st century (2041-2060). Next, the GCM outputs will be incorporated into the SWAT model to assess the climate change impact in Malawi. Modeling water balance under various climate change scenarios is expected to allow farmers/policy makers to plan and adopt proactive anticipatory adaptation measures to ensure crop productivity and food security for the future.

2. INTRODUCTION

Malawi is dominated by smallholders who rely on rain-fed subsistence farming for their livelihoods. Climate change has exacerbated their vulnerability and amplified food insecurity. Two major climate change threats to food production systems are heat and moisture stresses to the crops. All the GCM models suggest a general increase in temperature for the region in the future; however, the models disagree on the general magnitude and direction of change in precipitation. Though the GCM models provide spatial information on projected change in temperature and precipitation, they do not provide any information on how the land and water resources will be impacted by the global warming. It is imperative to project the change in moisture balance in the watersheds to understand how water use and planning may be affected under future climate conditions. To estimate the potential crop moisture stress and formulate proactive adaption measures, an estimation of various crop-production related soil-water parameters is also needed.

This study aims to use SWAT models to assess the impact of climate change on water resources and crop-production-related water parameters at sub-watershed and watershed scales in Malawi. By comparing the baseline water balance (1981-2000) with future water balances (2041-2060), the impact of climate change on evapotranspiration, soil water content, water percolation, surface runoff, base flow and water yield will be assessed. The projected impact on these parameters will enable farmers to plan water conservation measures, water harvesting operations, and irrigation planning to maintain sustainable food production. Currently, international development agencies, such as African Development Bank (2013), are working with the government of Malawi to bring more agricultural areas under irrigation. Therefore, this study is expected to provide information that will enable concerned stakeholders to plan climate change adaptation measures based on informed decision-making.

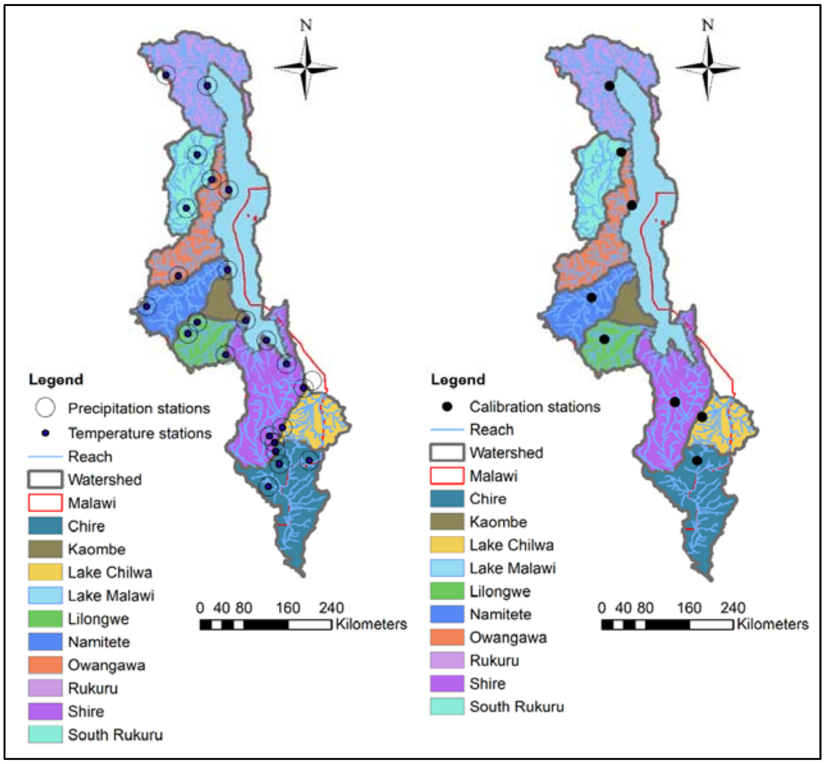
3. METHODOLOGY

We acquired 30 m global digital elevation data, 400 m global land use data, and 30 arc-second Harmonized World Soil Data, and created respective databases for use in building hydrological models. We also obtained daily stream flow data from 48 gauging stations and monthly stream flow data from two gauging stations at various locations throughout Malawi. However, the observed stream flow data obtained were mostly from the period prior to 1990s. We obtained meteorological data from 26 monitoring stations (Figure 6) and used them to construct hydrological models under current conditions.

Malawi was divided into 10 watersheds, out of which we are examining eight (where observed streamflow data were available for calibration and validation) using the SWAT model. In order to ensure accurate model performance, first, the hydrological parameters were adjusted until the simulated stream flow obtained from the models was within an acceptable range of observed values (calibration procedure).1 Then the model performances were tested for the new time period without adjusting any parameters (validation procedure). These simulations are computationally intensive and we used MSU's High Performance Computer Center to proceed with the simulations. After completing the calibration and validation, we ran the models on a daily time-step for 20 years (1981-2000), which will serve as a base period and will be compared with the future climate scenarios.

[1] Peak flows are notoriously difficult to replicate, and the selection of calibration and validation time windows can alter the accuracy of model results, but that is limited by data availability.

Figure 6. Watersheds in Malawi and Weather Stations Used for the SWAT Model



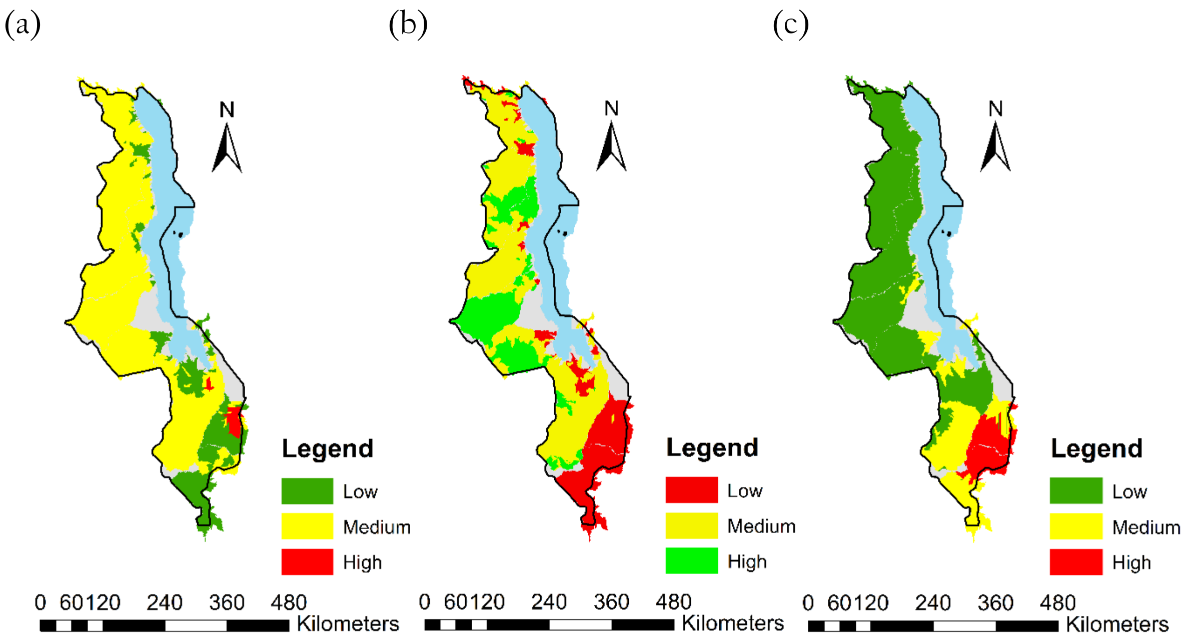
Source: Boundary data obtained from FAO 2000.

4. FINDINGS

Despite the restricted time window available for building the hydrological models, the SWAT models satisfactorily reproduced the stream flow for the calibration and validation periods. Model simulation results were statistically compared with the observed data by using Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS) and the root mean square error to the standard deviation of measured data (RSR) (Moriasi et al. 2007). NSE, PBIAS, and RSR values ranged from 0.55 to 0.8, -6.1 to 29.6 and 0.45 to 0.67, respectively, which were within the acceptable range for the monthly calibration.

Figure 7 shows 20-year (1981-2000) average annual evapotranspiration, soil moisture content and surface runoff obtained through SWAT modeling. The simulation captured the spatial and temporal variability of evapotranspiration, soil water content, water percolation, surface runoff, base flow, and water yield. For example, concerning soil moisture content, evapotranspiration, and surface runoff, higher values were observed in November-March and lower in May-September. A more detailed analysis of the data is yet to be completed. These findings will serve as baselines for our climate change impact assessment.

Figure 7. Long-term Annual Averages of (a) Evapotranspiration, (b) Soil Moisture Content, and (c) Surface Runoff



Source: Author's calculations with data from SWAT model.

5. CONCLUSIONS AND LIMITATIONS

We have completed building, calibrating and validating the SWAT hydrological models to establish a baseline for assessing the water balance and climate change impacts on crop water availability in Malawi. These modeling efforts tie directly to the much-needed characterization of uncertainty for Malawi's land and water resources and feeds directly into planning adaptation measures to ensure food security for the future.

Data availability was the major hurdle encountered in the modeling process. Meteorological data were available from only 26 stations in the country. Denser meteorological data would have improved the model predictability. Stream flow data were obtained from Global Runoff Data Center, which were mostly from before the 1990s. Several contact attempts to the Malawian Water Resources Department failed, and thus, the most recent stream flow data could not be obtained.

6. NEXT STEPS AND FOLLOW-UP

Our next step is to incorporate various climate change scenarios into the models in order to assess the climate change impacts on land and water resources in Malawi at both the watershed and sub watershed scale. We have downloaded GCM outputs from five climate models on monthly time-step from Earth System Grid Federation. We will downscale these datasets using the delta method and correct them using the quantile bias correction technique. These datasets will be used to create the future temperature and precipitation time series (2041-2060). The SWAT model will be run on these new sets of data and the model outputs will be compared with the base model outputs. The result will be a quantitative description of the impacts on evapotranspiration, soil water content, water percolation, surface runoff, and water yield under climate change and identification of the most vulnerable places in terms of water availability for crop production. The modeling process may be replicated as needed for assessing the impact of climate change in water balance in other countries as well. Both the calibrated models and the results of the modeling exercises will be available to Lilongwe University of Agriculture and Natural Resources (LUANAR) for continued use and improvement in managing water use for agriculture and human consumptions. This data will also be useful to USAID and GDL for applications where future projections of water availability are needed to improve agricultural yield predictions.

C. LAND USE ANALYSIS

1. INTRODUCTION

Land use in Malawi is heterogeneous and complex and the drivers of variability in most of the regions are unclear. We have compiled crop yield data from various economic sources (FAO, World Bank, etc.) and produced scatterplot matrices to assess the level of correlation between reported yield and remotely sensed vegetation (based on NASA Moderate Resolution Imaging Spectroradiometer (MODIS) land products). We are primarily seeking to understand how agricultural productivity and land use are changing over space and time. This relates to the original objectives by identifying the spatial heterogeneity of yield differences and yield gaps, and ties to the overarching theme of assessing food security through combining local-scale understanding with broader remotely sensed trends.

1.1. Land Classification Uncertainty

Land use across Malawi is a mosaic with agricultural land use the most prevalent. Multiple land use types coexist: intercropping, tree crops mixed with row crops, and patchworks of different farming types. This makes land use difficult to categorize at any but the finest of spatial scales. Agriculture is also rapidly changing and extensifying. This complex, mixed-use approach to cropping tends to make classification difficult from both economic and remote sensing perspectives. The land use maps produced by various agencies (GlobCover, MODIS, IFPRI, FAO, etc.), given the methodologies they use, are unable to capture the intricacies of variation and the changes in land use that take place.

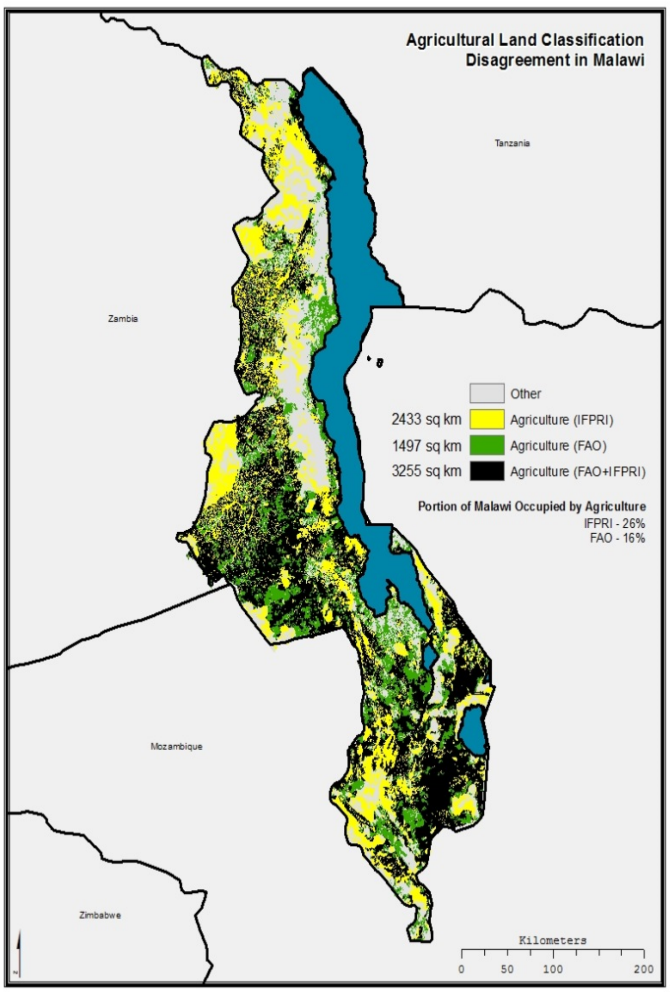
Crop models such as the Decision Support System for Agrotechnology Transfer (DSSAT) and SALUS rely upon accurate assessments of agricultural land in order to make accurate yield predictions. The inherent uncertainty in these land cover datasets propagates into crop yield predictions. There is a gap in research between coarse-scale land mapping and site-specific crop modeling that needs to be resolved.

2. METHODOLOGY

Figure 8A is a comparison of two land cover assessments by the International Food Policy Research Institute (IFPRI) and the Food and Agriculture Organization (FAO), and illustrates the degree of disagreement between the data [for a more detailed discussion see Messina (2015)]. The FAO dataset is a composite of land classified as agriculture for datasets released for 2000 and 2010 and the IFPRI dataset is from 2002. Agriculturally relevant land use classifications were extracted from the datasets and layered to show where the datasets agree and disagree. According to the FAO, agriculture accounts for a total of 16% of Malawi's land area, 10% less than the percentage reported by IFPRI. Whether methodological or political, there are clear differences in the production and accuracy of these data.

Figure 8. Summary of Disagreement between Multiple Land Use Datasets as to What is or is not Agriculture

8A. Classification Disagreement



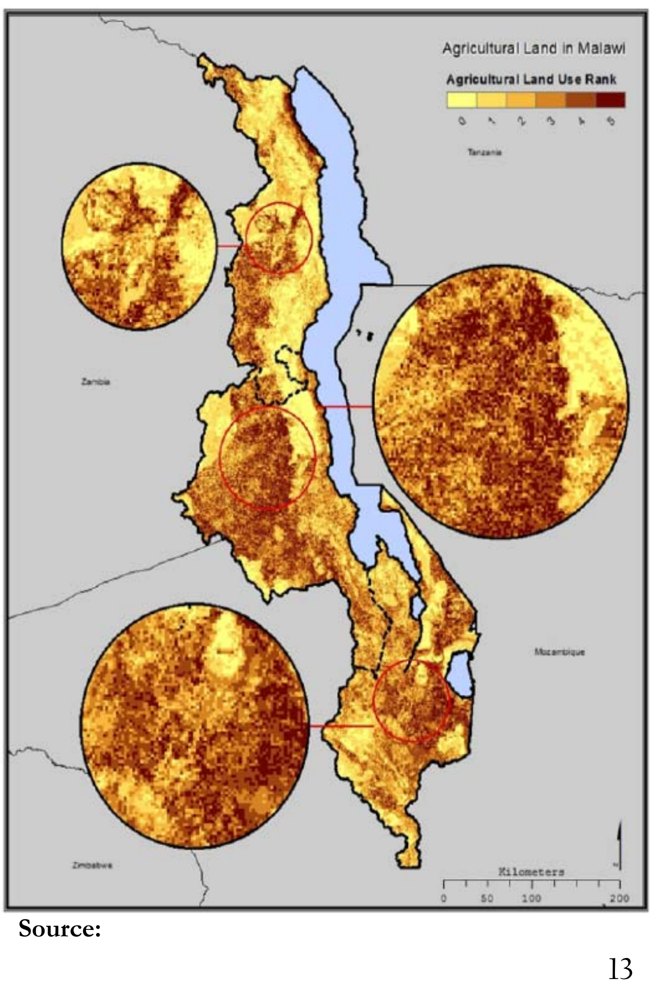
Source:

3. FINDINGS

We are assessing biophysical variability on agricultural land—variables that relate to agriculture (net primary productivity, normalized difference vegetation index, land surface temperature, elevation, etc.). In order to assess biophysical variability on agricultural land and minimize uncertainty, an agricultural land use confidence map was developed. We are not improving any individual land cover map or changing methodology. We are taking a set of land use/land cover maps and comparing them (they are all very different) in order to identify areas where the maps agree. For our analyses (especially crop modeling), we need to be certain that we are sampling on agricultural land.

Where all five datasets agree that an area is agriculture, we are most confident that it is indeed agriculture. Five land use products—including FAO (2000/2010), MODIS (2001-2010), GlobCover (2005-06/2009), GLC (2000), and IFPRI (2002)—were compiled into a singular 1-kilometer resolution agricultural land use map, matching the spatial resolution of the MODIS satellite imagery. The grid is structured such that an area with rank 0 is where none of the datasets classifies that area as agriculture and a ranking of 5 is where all datasets agree that an area is classified as agriculture. This is shown in Figure 8B. Figure 8A illustrates the great differences between two land cover maps; it shows that we do not really know where agricultural land is. Figure 8B shows a map we developed to help minimize the uncertainty of our sampling method. Rank 5 indicated that all five datasets agree that a given area is classified as agriculture. If we sample points only on rank 5, we can be relatively confident that we are actually capturing agricultural land.

8B. Land Use Uncertainty Minimization



Source:

3.1. Conclusions

Uncertainty and scaling problems (i.e., where different trends appear if measured at different scales) limit agricultural predictability in Malawi (scaling here refers to trends that vary across time and space at different scales). Predictions are critical to making useful decisions about allocating resources to improve production and yield, and scaling up of improved agricultural technologies (i.e., in the sense of promoting adoption by a larger number of farmers across a wider geographical area) is frequently cited as the main solution to reducing food insecurity in southern Africa.

In an effort to get a firmer handle on these concepts, we are seeking case studies through personal contacts and the literature where efforts to scale up the adoption of improved agricultural production technologies have occurred within, but not limited to, southern and eastern Africa, particularly through projects aimed at subsistence and smallholder farmers. The goal is to clearly articulate a climate-sensitive framework necessary for contextualizing proposed efforts to leverage food systems innovations to scale staple crop production (e.g., the climate resilient maize initiative).

There are potential interactions with other GCFSI projects when the modeling and uncertainty assessment are completed, particularly with the marketing and economic activities. These climate changes may shock or alter economic activity related to food security. In addition, exploring issues of scale should illuminate key locations for better and more sensitive data gathering to be undertaken by LUANAR for better characterization of land use, ecological processes, and refinement of remote sensing data. All of these data will reduce uncertainty, better illustrate errors across different scales, and improve accuracy and precision of agricultural predictions.

3.2. Next Steps and Follow-up

Expected deliverables: presently, there are three papers planned for completion by the summer of 2015 as a result of this work. We have several specific tasks to complete this project year. First, productivity trends of Malawi need to be calculated at varying scales (from 100m to the aggregate national level). This includes using our remotely sensed vegetation data to validate crop modeling and to identify areas where crop model errors are significant. The use of remote sensing data as a separate, independent measure of food production will allow us to identify areas of consistently productive land and areas of marginal land. Being able to identify marginal lands also will allow us to target some of the biophysical mechanisms behind changes in yield.

Further, we need to assess land cover/land use during the peak of the growing season to calibrate and refine our remote sensing estimates. We will then need to identify already-existing sources of yield data (FAO and otherwise) and connect those measurements to crop model results and remotely sensed estimates.

Finally, we will aggregate these results by developing a multi-disciplinary manuscript on integrating processes that operate at different scales in agriculture, and offer a climate-agriculture technology transfer course at LUANAR in Lilongwe in March 2015.

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