



APPLIED GEOSOLUTIONS, LLC

Mozambique: Agricultural Weather Risk Mapping Final Report

World Bank Project #: 7159460

Project PI: Nathan M. Torbick

World Bank POC: Carlos E. Arce

2011

ALL ACP AGRICULTURAL COMMODITIES PROGRAMME



ACP GROUP OF STATES



EUROPEAN COMMISSION



Mozambique: Agricultural Weather Risk Mapping

Applied GeoSolutions, LLC
Vendor #: 127285
87 Packers Falls Rd
Durham, NH 03824



APPLIED GEOSOLUTIONS, LLC
www.appliedgeosolutions.com

Project PI: Nathan Torbick
Email: torbick@agsemail.com
Phone: (603)659-2392



World Bank Contract #: 7159460
World Bank POC: Carlos E. Arce

All ACP Agricultural Commodities Programme



ACP Group Of States



European Commission

This report presents technical methodologies and project results for World Bank project #: 7159460 Mozambique: Agricultural Weather Risk Mapping by Applied Geosolutions vendor #: 127285. This final report summarizes mapping of homogenous weather and agroclimate regions, crop suitability mapping, crop vulnerability mapping, and field validation project outcomes as of December 1st, 2011. Accompanying this report are a summary slideshow presentation, executive summary, and digital GIS data files. Please cite this document as: Torbick, N., Ingraham, P., Hessions, S., Ge, J., Mugatha, S. Arce, C. 2011. Report for Mozambique: Agricultural Weather Risk Mapping, v.6, pp. 90.

Overview	7
Project Overview	8
Goal	8
Summary Approach	8
Objectives	8
Task 1: Mapping homogenous zones	9
Task 2: Crop suitability	34
Task 3: Crop vulnerability	39
Task 4: Crop suitability index	44
Acknowledgements	39
References	39
Appendix 1: Monthly TRMM Province averages	56
Appendix 2 Monthly LST Province averages	58
Appendix 3: Digital elevation model	60
Appendix 4: UK predictions and standard errors	61
Appendix 5: LST predictions and standard errors	62
Appendix 6: 10 year average climate – PCA	63
Appendix 7: 10 year average DJF climate - PCA	64
Appendix 8: 10 year average MAM climate - PCA	67
Appendix 9: 10 year average JJA	69
Appendix 10: SON climate - PCA	71
Appendix 11: 10 year average climate: K-means	73
Appendix 12: 10 year average climate DJF: K-means	74
Appendix 13: 10 year average climate MAM: K-means	75
Appendix 13: 10 year average climate JJA: K-means	76
Appendix 15: 10 year average climate SON: K-means	77
Appendix 16: Soil: PCA	78
Appendix 17: Climate & Soil: PCA	80
Appendix 18: Climate & Soil: K-means	87
Appendix 19: CSI by clusters	89
Appendix 20: CSI and CVI scenario 2	90
Figure 1: Project framework	8
Figure 2: Monthly satellite weather observations	10
Figure 3: Seasonal weather variability	11
Figure 4: Weather station locations	14
Figure 5: UK PPT & SE	16
Figure 6: Residual plots for TRMM PPT	18

Figure 7: Residual plots for OK PPT	18
Figure 8: Residual plots for UK PPT	19
Figure 9: UK Tmax & SE	21
Figure 10: Tmax UK residuals	23
Figure 11: Tmax residuals for LST	24
Figure 12: OK residuals of Tmax	24
Figure 13: Homogenous weather and agroclimate clusters	27
Figure 14a: TRMM PPT and MODIS LST by cluster	28
Figure 14b: Seasonal TRMM PPT and MODIS LST by cluster	29
Figure 15: DNDC model framework	31
Figure 16a: Crop suitability indices	34
Figure 16b: Optimized crop suitability indices	35
Figure 16c: Crop suitability indices comparison	36
Figure 17: Crop vulnerability indices	40
Figure 18: CSI and CVI comparisons	41
Figure 19: All crops CVI	42
Table 1: Monthly TRMM PPT tendencies	12
Table 2: Monthly MODIS LST tendencies	12
Table 3: Correlation between station PPT and TRMM PPT	14
Table 4: Summary PPT regression results	15
Table 5: Summary PPT estimates	17
Table 6: PPT RMSE	17
Table 7: Correlation between station PPT and MODIS LST	19
Table 8: Regression models for UK of TMAX	20
Table 9: Summary LST regression results	22
Table 10a: RMSE for Tmax & Tmean	22
Table 10b: RMSE for Tmax & Tmean	23
Table 11: Cluster names	28
Table 12: DNDC parameters	32
Table 13: Climate scenarios	39
Table 14: Scenario vulnerability	39
Table 15: Sampled crop rankings	45
Table 16: Crop frequency by sample population	45
Picture 1-5: Field pictures of surveys	49-50

Acronyms

AGS	Applied Geosolutions
AIC	Akaike Information Criterion
ARD	Agriculture and Rural Development Department
ARMT	Agricultural Risk Management Team
BD	Bulk Density
BS	Base Saturation
C	Carbon
CC	Calcium Carbonate
CEC	Cation Exchange Capacity
CF	Clay Fraction
CGIAR	Consultative Group on International Agricultural Research
COST	Commercial Off-the Shelf Technology
CSC	Cross Sectional Convexity
CSI	Crop Suitability Index
DC	Drainage Class
DEM	Digital Elevation Model
DJF	December January February
DNDC	DeNitrification-DeComposition
FAO	Food and Agricultural Organization
FDG	Focus Discussion Group
FL	Factor Loading
GC	Gravel Content
GDAL	Geospatial Data Abstraction Library
GDP	Gross Domestic Product
GIS	Geographic Information Systems
GMAO	Global Modeling and Assimilation Office
GOM	Government of Mozambique
GV	Ground Validation
HWSD	Harmonized World Soil Database
IIAM	Agricultural Research Institute of Mozambique
IIASA	International Institute for Applied Systems Analysis
ILRI	International Livestock Research Institute
ITCZ	InterTropical Convergence Zone
JAXA	Japan Aerospace Exploration Agency
JJA	June July August
KII	Key Informant Interview
LC	Longitudinal Convexity
LPDAAC	Land Processes Distributed Active Archive Center
LULC	Land Use Land Cover
LST	Land Surface Temperature
MAM	March April May
MC	Maximum Curvature

MERRA	Modern Era Retrospective-Analysis for Research and Applications
MODIS	Moderate Resolution Imaging Spectroradiometer
MOA	Ministry of Agriculture
N	Nitrogen
NASA	National Aeronautics and Space Administration
OC	Organic Carbon
OGC	Open Geospatial Consortium
OK	Ordinary Kriging
OLS	Ordinary Least Squares
PC	Profile Convexity
PCA	Principal Components Analysis
PPT	Precipitation
QAQC	Quality Assurance Quality Control
RS	Remote Sensing
RMSE	Root Mean Square Error
SF	Sand Fraction
SIF	Silt Fraction
SOC	Soil Organic Carbon
SON	September October November
SRTM	Shuttle Radar Topography Mission
TEB	Total Exchangeable Bases
TRMM	Tropical Rainfall Measuring Mission
TMAX	Temperature Maximum
TMEN	Temperature Mean
TMI	TRMM Microwave Imager
TMIN	Temperature Minimum
UK	Universal Kriging
WB	World Bank
WIST	Warehouse Inventory Search Tool
WSC	Water Storage Capacity
VIRS	Visible and Infrared Scanner

Project Overview

The Agricultural Risk Management Team (ARMT) of the Agriculture and Rural Development Department (ARD) at the World Bank has agreed with the Ministry of Agriculture (MOA) of Mozambique to provide technical assistance in various aspects related to agriculture risk management. The technical assistance that the World Bank is planning to provide to the MOA needs to serve as the basis for the government and private sectors to identify and put in place measures to start managing agricultural risks in a more informed manner and under an agreed framework.

The agricultural sector in Mozambique is dominated by 3.2 million smallholder families of which the majority of smallholders grow food crops, and about 16 percent also participate in cotton and tobacco out-grower schemes. This is the major source of livelihoods, especially in rural regions, as rural smallholders provide about 95% of agricultural Gross Domestic Product (GDP). The growth of the agricultural sector has helped reduce poverty and build rural infrastructure from both food and cash crops. There is significant room to enhance efficiency because only 10% of the 36 million arable hectares are cultivated and technologies and organization are lacking (i.e., little irrigation, low productivity). However, climate vulnerability and risk present a tremendous threat to Mozambique's agricultural sector and little has been done to address risk or establish a framework for crop insurance programs and agricultural monitoring.

Regional climate change, such as warming Indian Ocean temperatures reducing rainfall, is expected to continue to threaten agricultural yields in the foreseeable future (Funk et al 2008). The Mozambique Agricultural Census 2008 (TIA 2008) shows that farmers face production risks related to floods, droughts, and cyclones and it provides some dimension of importance for various agricultural regions. This census found that many farms are under threat and are under producing. Estimates for average actual yields (t/ha) for maize, cassava, cotton, sorghum, beans, and rice are already well below the estimated average potential yields (Loening and Perumalpillai-Essex 2005). Despite the recognized importance of production risks, preliminary discussions with various stakeholders in the agricultural sector reveal that there is hardly any technical analysis done in risk identification and risk exposure in agriculture, nor any systematic attempt at quantifying the losses produced by the occurrences of those risks. This situation makes it difficult for the authorities or the private sector to start introducing appropriate risk management practices. Further, donor institutions' strategies and investments will benefit from considering the spatial distribution of weather risks and crop specific vulnerabilities for a given region (Moore et al 2011).

In the past, whenever an adverse catastrophic event has taken place, the MOA has relied on an ad-hoc system to collect financing from the Ministry of Finance and donors to make a pool of resources to deliver support to affected farmers. The MOA is therefore very interested in identifying and designing a risk management framework that will allow the public sector to implement risk management measures in a more planned manner and in partnership with the private sector to start managing identified agricultural risks.

The World Bank and Government of Mozambique (GOM) need risk mapping assessment of the agricultural sector in Mozambique with the objective to aid policy makers and planners to identify the key crops and exposures to loss and which might be selected for designing a national agricultural risk management strategy and for future pilot crop insurance programs.

Goal & Objectives

The overarching goal of this project is to develop initial analysis and mapping products to begin to build a framework for addressing agricultural risks from adverse weather and climate change. The goal is to identify crop risks from weather and map vulnerability.

The technical objectives are to:

- Objective 1: Map homogenous weather and agroclimate zones
- Objective 2: Characterize crop suitability for major cash and food crops
- Objective 3: Assess crop vulnerability to weather conditions
- Objective 4: Carry out a field campaign to integrate calibration information

Summary Approach

We designed a work plan and methodology that addressed the Terms of Reference (ToR) in a systematic fashion considering the timeline, framework, and clients. In nontechnical terms, we used 1.) remote sensing and geographic methods to generate maps of weather zones and agroclimate zones, then 2.) compiled a suite of agronomic and bioclimate datasets to use a Geographic Information Science (GISc) approach and biogeochemical modeling to generate crop suitability indices. Following Components 1 and 2 we carried out 3.) modeling for major cash and food crops using climate scenarios to generate crop vulnerability indices and risk maps. To validate and improve modeling results, 4.) field validation and surveys were carried out and feedback was iteratively utilized to improve the precision of the crop risk maps. This approach is easily scalable and completely “operationalizable” so can contribute toward a national agricultural risk management strategy and crop insurance programs for Mozambique.

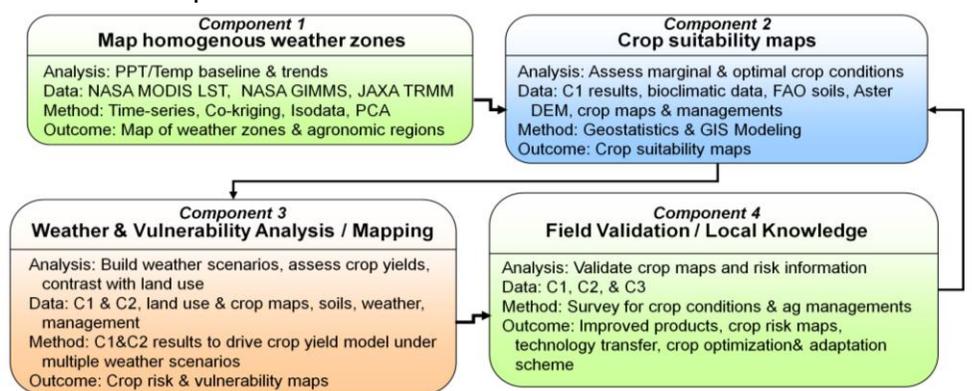


Figure 1. Conceptual approach to map agricultural weather risks for Mozambique.

Task 1: Map homogenous weather and agroclimate zones

Remotely Sensed Weather Data

Satellite observed rainfall and temperature data were obtained and analyzed for Mozambique to map spatiotemporal trends and homogenous weather- and agroclimate-zones. The first satellite data analyses focused on the use of monthly accumulated rainfall time steps from NASA's Tropical Rainfall Measuring Mission (TRMM). TRMM rainfall data used in this application has a 0.25 degree resolution, which is approximately 25 km spatial resolution over Mozambique. TRMMs precipitation estimates are based on both active and passive microwave instruments. TRMM estimates employ the Visible and Infrared Scanner (VIRS) and TRMM Microwave Imager (TMI) instrumentation to provide quantitative rainfall information. TMI quantifies water vapor, cloud water, and rainfall intensity in the atmosphere by characterizing minute amounts of microwave energy emitted in the lower boundary layer.

The TRMM Ground Validation (GV) program operates from the NASA Goddard Space Flight Center. This team uses gauge, station, field, and modeled data to calibrate and validate precipitation (ppt). These ground data are used to improve the rain rate interpretation algorithm. Wolff et al. (2004) reported the monthly rainfall accumulation scheme of TRMM matches well with ground ppt measurements with +/-5% between convergence of field gauge measurements and TRMM data.

Land surface thermal data was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument onboard the Terra (descending) and Aqua (ascending) satellite platforms. The MODIS sensor collects measurements in 36 spectral bands every 1-2 days at native spatial resolutions of 1km for Land Surface Temperature (LST) products. MODIS products are available from the Warehouse Inventory Search Tool (WIST) at the Land Processes Distributed Active Archive Center (LPDAAC). The monthly products of MODIS MYD11C3 used in this study are composited from their fine temporal resolution data to provide higher quality observations. The MODIS MYD11C3 LST products utilized in this study have a spatial resolution (pixel size) of 0.05 degree, which is approximately 5 km gridded pixel size for the entirety of Mozambique. A period from 2002 to 2010 was utilized.

The MODIS LST products have been extensively refined and validated to provide precise and accurate information. LST accuracy is reported to be within 1K under clear-sky conditions in a range of ecosystems (Wan et al 2002, Wan 2008). Wan et al (2004) assessed MODIS LST against *in situ* field measurements for twenty clear sky cases in 2000-2002 and found LST to be better than 1C in the range of -10 – 50C. Validation across multiple sites incorporating wide ranging ecosystems and atmospheric conditions has consistently shown that MODIS LST products are within ± 1 K in the range 263-322K. Further, comparisons between V5 LSTs and in-situ values in 47 clear-sky cases (in the LST range from -10 °C to 58 °C and atmospheric column water vapor range from 0.4 to 3.5 cm) indicate that the accuracy of the MODIS LST product is better than 1 K in most cases (39 out of 47) and the root of mean squares of differences is less than 0.7K for all 47 cases or 0.5K for all but the 8 cases apparently with heavy aerosol loadings (Wan et al. 2008). Thus, the precision, accuracy, and reliability of MODIS LST makes it well-suited for assessing land surface temperature zones in

data poor regions. Both MODIS LST and TRMM PPT were preprocessed to identical 0.05 spatial resolution and monthly time steps for all of Mozambique to have consistent inputs for analysis. It is noted that approximately nine years of monthly observations are utilized and thus interpretations for long term trends are limited; however, variability during this period provides insight on weather risks as it relates to cropping calendar and inconsistent weather intensity and timing.

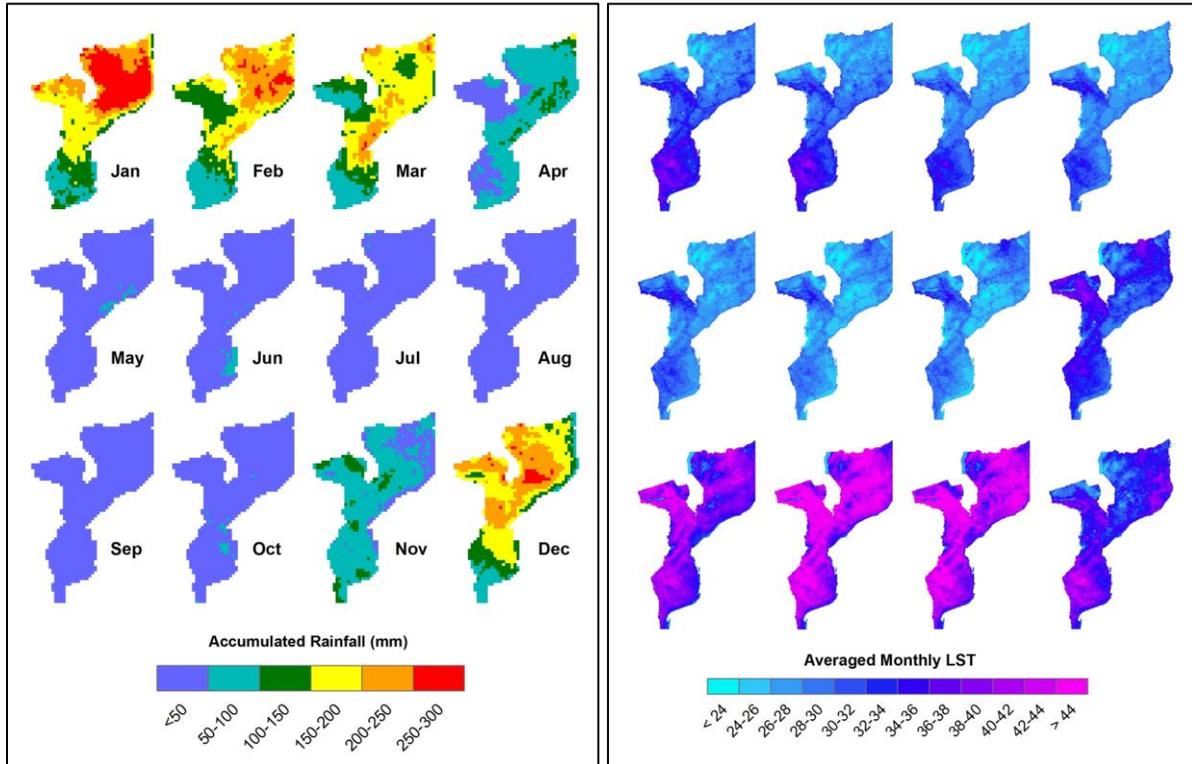


Figure 2: Monthly average accumulated rainfall (left) observed from TRMM and monthly average land surface temperature (right) observed from MODIS in Mozambique from 2002 to 2010. Generally, the remotely sensed climate products capture distinct seasons across Mozambique: a relatively wet and cooler season from November to April, and a relatively dry and hot season from May to September.

To define the length of dry season we generated a simple metric showing the number of months that are drier than nine year average (2002-2010), and the length of wet season defined as number of months that are wetter than average. The length of dry/wet and hot/cool seasons and their variability are shown in Figure 3. This analysis for the domain average for Mozambique was intended to provide a spatially crude indicator of weather variability. A similar approach was used to define length of hot and cool seasons. Number of dry months varies between 6 to 9 while the number of wet months varies between 3 and 5. In comparison, number of hot and cool months varies between 4 to 5 and between 7 to 8 respectively. This indicates that the inter-annual variability of rainfall conditions is greater than temperature conditions.

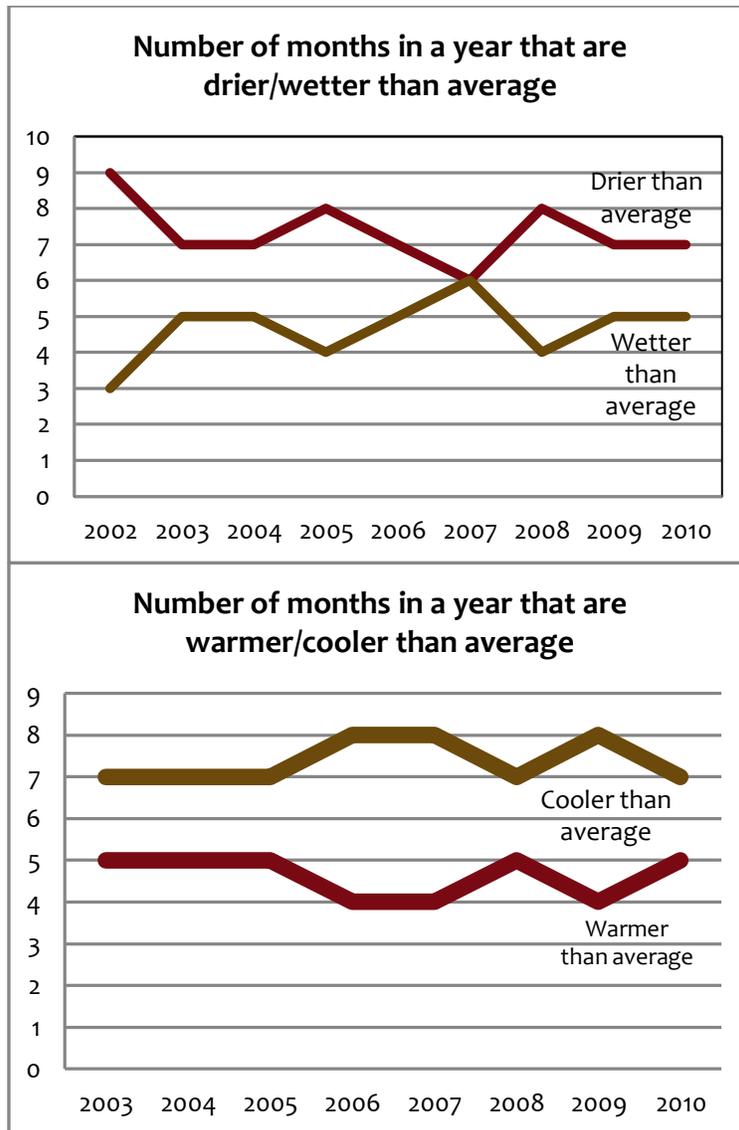


Figure 3: Length of dry/wet season (top) and length of hot/cool season (bottom).

The greater inter-annual variability of rainfall is also shown in the timing of peaks of rainfall and temperature conditions. Table 1 shows the wettest and driest months from 2002 to 2010, and Table 2 shows the hottest and coolest month. From these two tables, the hottest and coolest time in a year remains relatively constant (October and June). However, the driest and wettest time in a year changes substantially. The period with the highest accumulated monthly rainfall appears between December to March, while dry periods varies between May to September.

Table 1: The month in a year that receives maximum and minimum rainfall

	Wettest month	Driest month
2002	Jan	May
2003	Jan	Aug
2004	Dec	Aug
2005	Dec	Aug
2006	Mar	Sep
2007	Dec	Aug
2008	Jan	Jul
2009	Feb	Sep
2010	Feb	Sep

Table 2: The month in a year that has the highest and lowest temperature

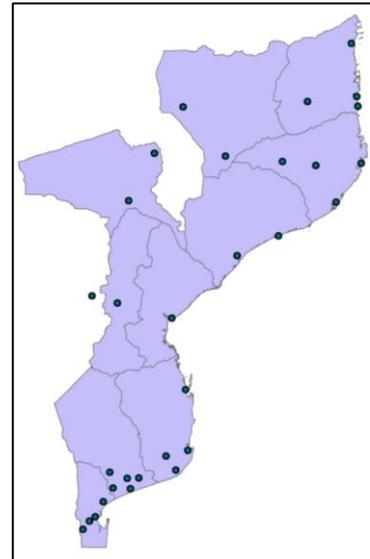
	Hottest month	Coolest month
2003	Oct	Jun
2004	Oct	Jun
2005	Nov	Jul
2006	Oct	Jun
2007	Oct	Jun
2008	Oct	Jun
2009	Oct	Mar
2010	Oct	Jun

This regional analysis shows that rainfall totals and rainfall seasonality have displayed greater variability than temperature patterns for Mozambique during the past decade. This indicates that rainfall intensity and timing is challenging to predict thus making agricultural planning difficult. Planting dates and growth rates are affected by this variability and cause various stressors (i.e., nitrogen demand and fixation, soil thermal degree days, water deficit) that can reduce yields. In Mozambique, for example, several varieties of maize are susceptible to water logging which impacts nutrient uptake while drought retards pollen grain shading. Concordantly, if temperature variability or trends increase a shortening in growing time or increase in water stress can occur. This process compounds the risk posed from rainfall variability. Variability in rainfall, and to a lesser degree temperature, thus pose risks to maize production in Mozambique. In Inhambane, Manica, Nampula, Niassa, Tete,

and Zambezia, where many small scale farmers grow maize, production will potentially be affected by the variability. This domain averaged example highlights weather risks from variability; however, impacts vary by geography and crop type. For example, in highlands warmer temperatures might create improved maize yields at the same time reduce cash crop yields. The economics of shifting cultivation and potential changes to income thus need to be factored when considering rainfall variability risks and productivity. This also highlights the need for spatially explicit risk maps for each key crop when constructing an agriculture monitoring framework.

TRMM & LST geostatistical calibration / validation

Weather station data was utilized to calibrate and validate (cal/val) the remote sensing weather products (figure 4 insert: weather station locations). Stations (n=32) were received through the project partner and had only gone through preliminary Quality Assurance Quality Control (QAQC). Attributes included daily accumulated ppt, maximum daily temperature (Tmax), and minimum daily temperature (Tmin). Initial QAQC for the modeling tasks carried out for this project was applied. Records in which Tmin were a magnitude higher than Tmax were eliminated as were records in which Tmax were a magnitude lower than Tmin. Records with a difference between Tmax and Tmin four orders of magnitude or greater than Tmin were eliminated. Temps that were greater than four times the average of Tmax were eliminated. Approximately 30 stations existed in the initial dataset after preliminary QAQC. Two stations were eliminated due to geolocation issues. Secondary QAQC processing eliminated stations with more than 50% of data missing and these records were not used for regression and geostatistical analyses, resulting in approximately 24 stations available as cal/val.



The TRMM datasets were aggregated over time to reflect 10-year average annual precipitation and 10-year average seasonal precipitation (months DJF, MAM, JJA, SON). Station data sets were also aggregated using available data collected over the same time period. Correlation coefficients (R) were calculated between station precipitation data and TRMM precipitation data corresponding to station locations. Both data sets were aggregated to reflect a 10-year average annual precipitation, and 10-year average seasonal precipitation (DJF, MAM, JJA, SON) (or as best as possible with the stations given the temporal gaps). Coefficients of correlation range from 0.75 to 0.89 (table 3 insert: Correlation between PPT and TRMM). Squaring these values yields the coefficients of determination, which can be interpreted as the percent of variation in station ppt that is explained by variation in TRMM data. Coefficients of determination range from 0.56 to 0.78, indicating that the aggregated TRMM data explains between 56 and 78% of the variation present in the aggregated station data.

Correlation Coefficients Between Station PPT and TRMM	
	Correlation Coefficient R
AVGPPTSUM	0.7606745
DJFPPTSUM	0.892987
MAMPPTSUM	0.8656843
JJAPPTSUM	0.746823
SONPPTSUM	0.7607398

Regression modeling was completed to identify the best models for predicting average annual and average seasonal precipitation measurements at the station locations.

Independent variables that were considered included: elevation at a 5 km resolution, aspect, slope, longitudinal convexity, maximum curvature, and remotely sensed TRMM PPT and MODIS LST at corresponding time periods (annual or seasonal 10 year averages). Slope and aspect data were combined to calculate the eastern and northern components of the unit normal vector for inclusion in the regression analysis following established guidelines (Hutchinson 1998). These components were calculated at multiple scales (see Digital Elevation Model derivatives section).

Table 4: Summary PPT regression results.

Regression Models Used for Universal Kriging of PPT							
Dependent Variable	Coefficients	Estimate	Std. Error	t value	Pr(> t)	Mult R2	Adj R2
AVGPPTSUM	(Intercept)	2.429	1.673	1.451	0.1630	0.7876	0.7541
	avgdem5km	-0.001	0.000	-1.917	0.0704		
	AVGTRMM	0.051	0.008	6.187	0.0000		
	AVGLST	-0.172	0.045	-3.819	0.0012		
DJFPPTSUM	(Intercept)	-2.213	0.308	-7.185	0.0000	0.7375	0.7249
	DJFTRMM	0.015	0.002	7.68	0.0000		
MAMPPTSUM	(Intercept)	0.992	1.451	0.684	0.5032	0.9042	0.876
	avgdem5km	-0.109	0.042	-2.601	0.0186		
	p	0.384	0.153	2.508	0.0226		
	maxcurv	24.952	9.665	2.582	0.0194		
	MAMTRMM	0.032	0.004	8.666	0.0000		
	MAMLST	-0.117	0.042	-2.778	0.0129		
JJAPPTSUM	(Intercept)	6.671	2.265	2.945	0.0100	0.8713	0.8112
	avgdem5km	-0.026	0.051	-0.52	0.6108		
	p	0.322	0.202	1.599	0.1307		
	q	0.060	0.196	0.307	0.7628		
	longconv	-0.338	0.430	-0.788	0.4431		
	maxcurv	4.980	11.830	0.421	0.6798		
	JJATRMM	0.018	0.025	0.714	0.4863		
	JJALST	-0.226	0.061	-3.708	0.0021		
SONPPTSUM	(Intercept)	-0.593	1.746	-0.339	0.7384	0.7172	0.634
	avgdem5km	-0.135	0.077	-1.767	0.0952		
	p	0.374	0.282	1.33	0.2012		
	maxcurv	31.148	17.649	1.765	0.0955		
	SONTRMM	0.074	0.012	6.088	0.0000		
	SONLST	-0.062	0.041	-1.506	0.1504		

Summary results of the regression analysis and the selected regression models for the precipitation datasets show average annual and seasonal results (table 4). Several models were tested for each data set and a “best” model was selected using the Akaike Information

Criterion (AIC; Akaike, 1974). Summary regression results for selected PPT models are highlighted in table 4. Overall R^2 and adjusted R^2 values are relatively high, indicating that regression models using the remotely sensed TRMM data are able to represent a large portion of the variability observed in precipitation at station locations.

The range of estimated ppt amounts generated by ordinary kriging (OK) and universal kriging (UK) are summarized below, together with the range of actual station measurements and TRMM estimated amounts. TRMM shows slightly less variability as does OK whereas the actual data tends to have greater variability. This is not surprising considering the scale of measurements from local stations to remote sensing pixel (25km). TRMM slightly under estimates station ground truth annually and across seasons. UK has the highest maximum which is not surprising because the station data do not represent the full range of Mozambique attributes as represented by all the independent variables.

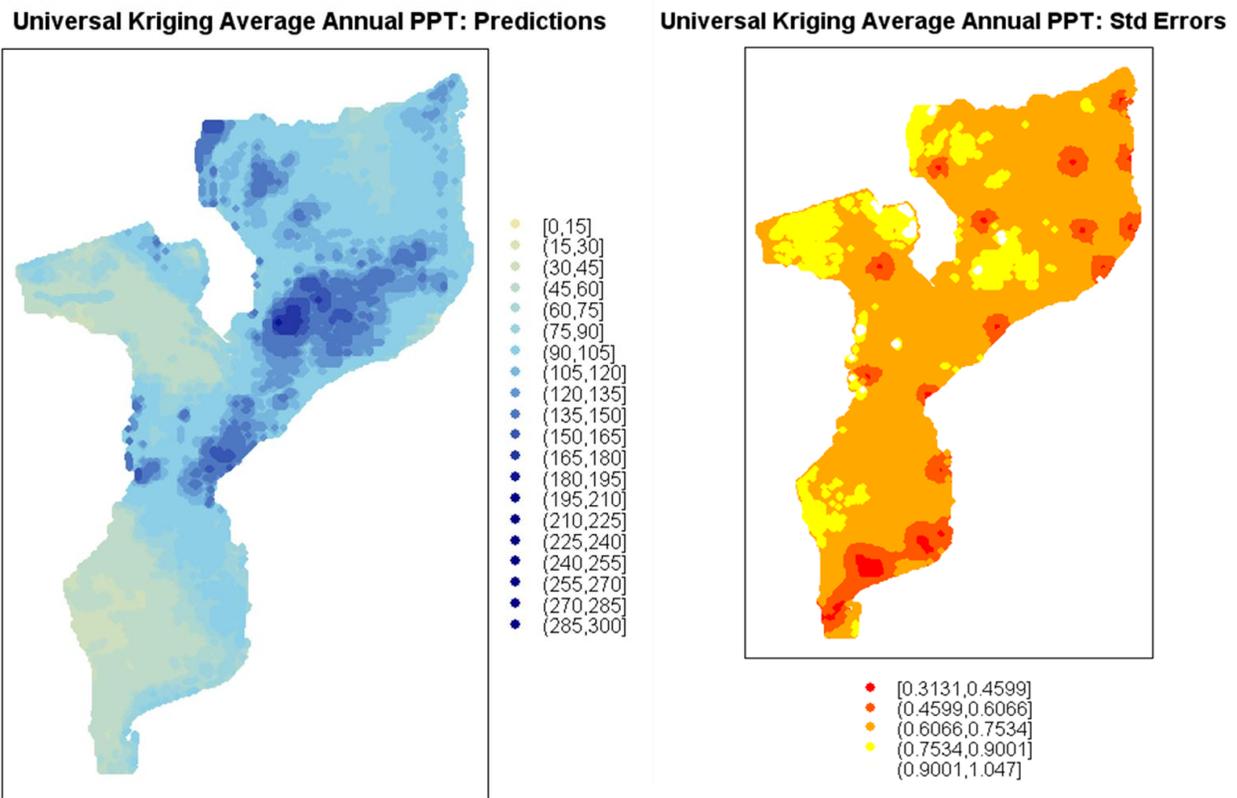


Figure 5. Universal kriging of precipitation data was completed using the independent variables identified in Table 4 by AIC. These average annual ppt predictions are at monthly intervals to match the input data. Predicted values for ppt are summarized in Table 5. Summary statistics are presented for actual observations and remotely sensed data as well as predicted values obtained through ordinary kriging and universal kriging (see appendices for details). As expected the uncertainty is lowest closest to the stations.

Table 5. Summary PPT estimates.

Summary of Predicted Values by Estimation Method							
Precipitation Data	Estimator	Minimum	1 st Quartile	Median	Mean	3 rd Quartile	Maximum
Average Annual	TRMM	46.9	55.75	63.3	68.52	80.75	105
	OK	44.72	74.21	82.73	79.26	87.23	126.3
	UK	42	56.14	99.02	88.27	104.7	181.6
	Actual	42	53.85	74.6	74.73	95.3	134.7
DJF	TRMM	84.1	96.85	132.7	144.8	174.7	266.3
	OK	71.09	127.2	205.3	177.4	218.5	282.2
	UK	67.3	153.7	235.2	219.5	282.2	400
	Actual	67.3	96.35	148.6	161	227	290
MAM	TRMM	40.1	58.5	70.5	75.25	88.9	120.8
	OK	38.09	77.47	86.01	84.03	94.35	153.2
	UK	27.9	60.31	89.63	90.55	115.5	191.6
	Actual	27.9	57.55	73.2	79.96	94.45	170.1
JJA	TRMM	6.2	12.95	16.9	17.81	22.75	28.3
	OK	3.064	15.77	21.6	24.57	35.58	65.15
	UK	1.9	11.07	16.39	20.14	26.64	91.13
	Actual	1.9	12.05	20.2	24.28	36.95	70.6
SON	TRMM	14.1	27.9	36.1	36.24	43.05	58.4
	OK	16.35	24.18	33.44	35.27	47.89	55.85
	UK	11.3	17.47	26.62	29.75	42.95	75.16
	Actual	11.3	24.35	36.9	36.69	49.15	64.2

Ability to predict station observations was evaluated using root mean squared errors (RMSEs) and maps of significant error terms. RMSEs provide a single, map-wide summary of error, whereas maps of significant result residuals can be used to evaluate spatial patterns in error terms. RMSEs are summarized in the Table 6 insert for precipitation. Universal kriging provided the lowest RMSE for average annual precipitation over the 10-year time period. RMSEs for the seasonal data sets were lowest in comparison directly to the TRMM data and predictions obtained through universal kriging. When using an “average annual” for modeling UK has the optimal results for predicting station data.

Root Mean Squared Errors (RMSEs)			
Precipitation Data	TRMM	Ordinary Kriging	Universal Kriging
Average Annual	16.74641	23.58774	14.29027
DJF	41.81239	60.98579	63.45015
MAM	17.60578	31.9632	17.01302
JJA	15.42051	16.15962	43.90769
SON	10.56648	11.53108	11.91236

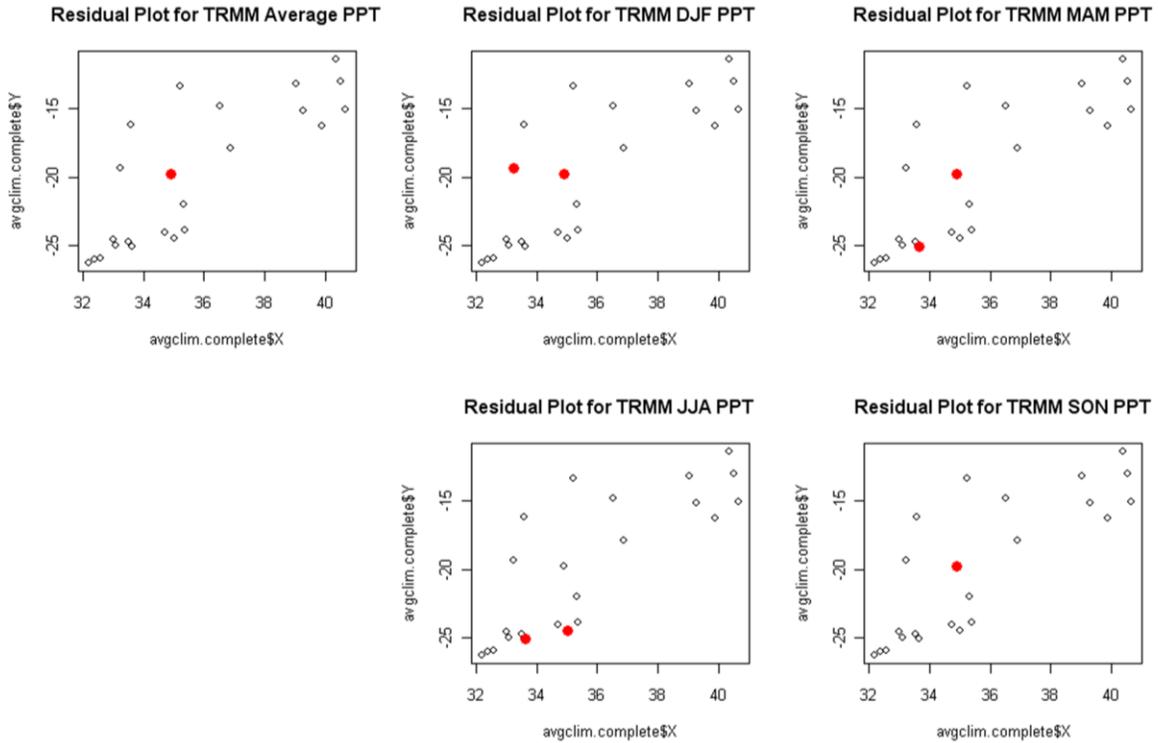


Figure 6. Residual plots for TRMM at annual and seasonal intervals highlight that only a few stations are significantly under predicted with little to no clustering of the residuals.

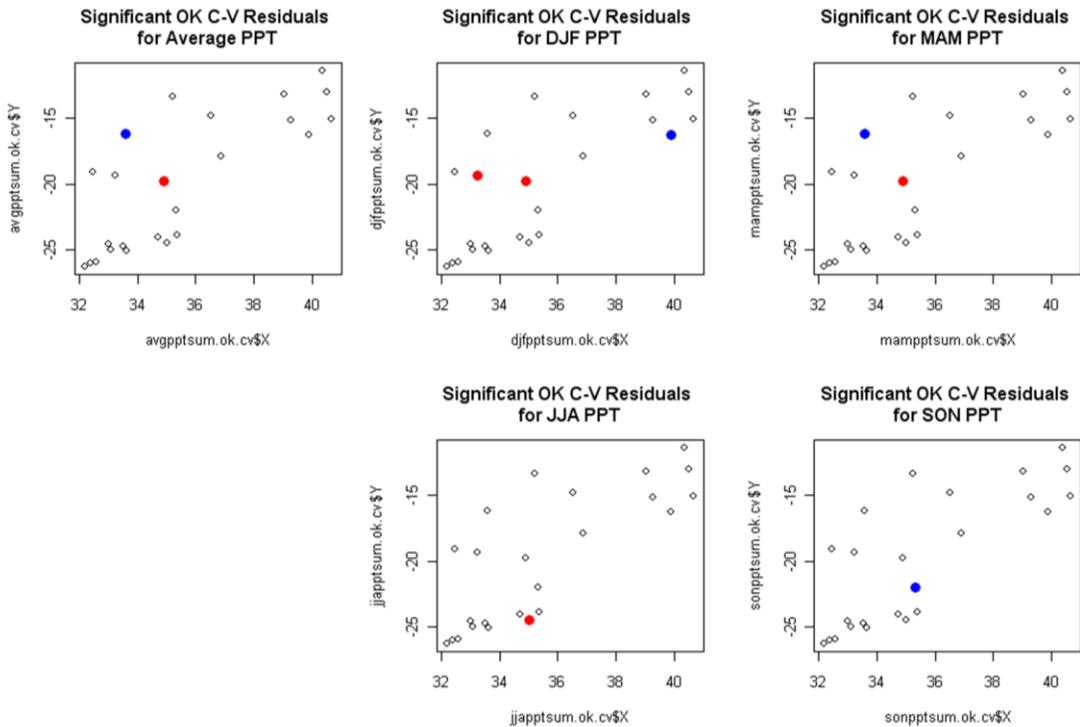


Figure 7: Residual plots for OK at annual and seasonal intervals show little to no significant clustering of the residuals.

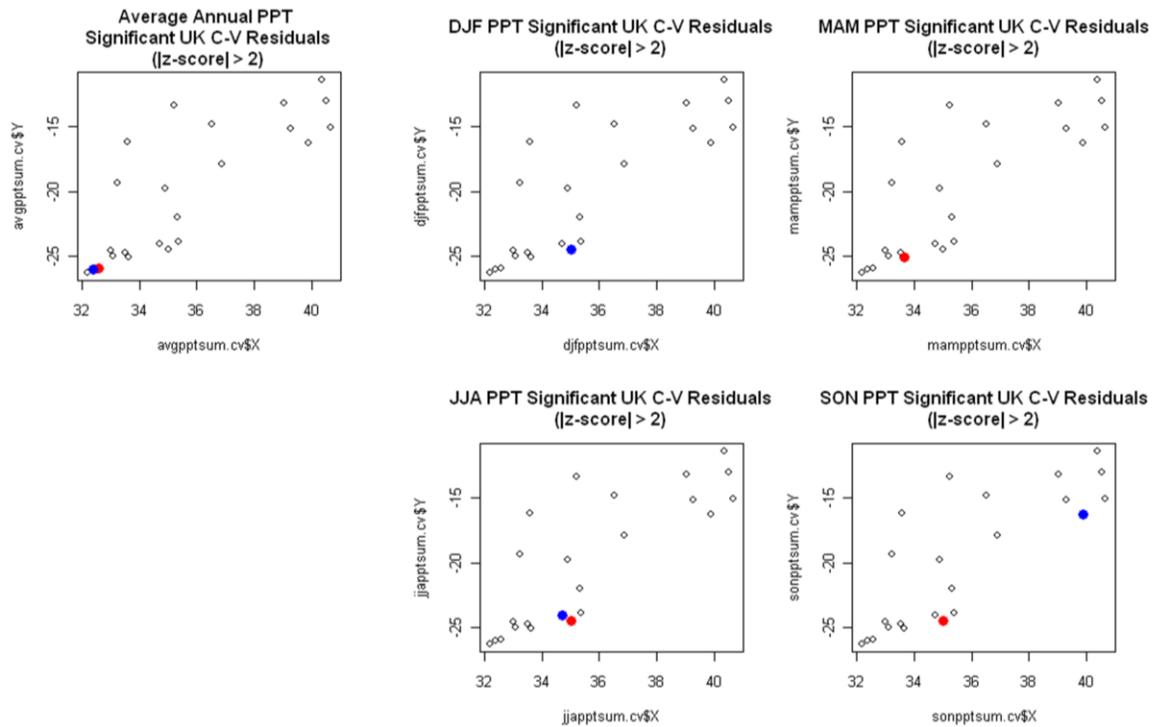


Figure 8: UK had the optimal annual average station prediction ability and plots indicate little to no significant clustering.

The MODIS LST data sets were aggregated over time to reflect a 10-year average annual temperature, and 10-year average seasonal temperature (DJF, MAM, JJA, SON). Station data sets (TMIN, TMEAN¹, and TMAX) were also aggregated using available data collected over the same time period. TMEAN¹ used in this modeling was an average of Tmax and Tmin. Correlation coefficients were calculated to identify the station temperature variable most highly correlated with MODIS LST data (table 7 insert). In all cases, TMAX was most highly correlated with MODIS LST; consequently, regression analyses and subsequent kriging were completed using TMAX observations from the QAQC weather station data.

	Correlation Coefficient R		
	TMEAN	TMIN	TMAX
Average Annual	0.439	0.164	0.700
DJF	0.506	0.273	0.675
MAM	0.614	0.429	0.761
JJA	0.544	0.342	0.736
SON	0.434	0.000	0.743

Table 8. Model used in UK of TMAX. The best models for average annual and for each season included elevation, remotely sensed ppt, and remotely sensed temp as significant predictors of T_{max}.

Regression Models Used for Universal Kriging of TMAX							
Dependent Variable	Coefficients	Estimate	Std. Error	t value	Pr(> t)	Mult R2	Adj R2
AVGTMAX	(Intercept)	11.924	2.863	4.166	0.0005	0.7695	0.7695
	avgdem5km	-0.003	0.001	-4.785	0.0001		
	AVGTRMM	0.044	0.014	3.163	0.0051		
	AVGLST	0.459	0.077	5.956	0.0000		
DJFTMAX	(Intercept)	22.036	2.912	7.567	0.0000	0.814	0.7846
	avgdem5km	-0.005	0.001	-6.054	0.0000		
	DJFTRMM	0.015	0.005	3.27	0.0040		
	DJFLST	0.244	0.076	3.225	0.0045		
MAMTMAX	(Intercept)	13.755	3.850	3.573	0.0020	0.709	0.663
	avgdem5km	-0.002	0.001	-2.057	0.0537		
	MAMTRMM	0.018	0.010	1.823	0.0840		
	MAMLST	0.487	0.112	4.353	0.0003		
JJATMAX	(Intercept)	9.723	3.245	2.996	0.0074	0.7836	0.7495
	avgdem5km	-0.002	0.001	-2.808	0.0112		
	JJATRMM	0.062	0.042	1.488	0.1532		
	JJALST	0.548	0.088	6.216	0.0000		
SONTMAX	(Intercept)	14.774	2.463	5.998	0.0000	0.7819	0.7474
	avgdem5km	-0.002	0.001	-2.519	0.0209		
	SONTRMM	-0.065	0.019	-3.456	0.0027		
	SONLST	0.483	0.063	7.644	0.0000		

It is clear that MODIS LST tends to overestimate TMAX results according to the data inputs and approach used in this application; the blue symbols indicate that the error terms (TMAX – MODIS LST) are significantly negative across the maps. The maps of residuals for universal kriging consistently identify fewer significant error terms than the maps for ordinary kriging, at least for station locations. However, both the OK and UK do a poor job at capturing the spatial patterns observed by the remote sensing observation due to the sparsely populated coverage of the station locations. The over estimation by MODIS is possibly due to the difference in measurements between ground station observations and MODIS LST product. Station temperatures are generally 1-2 meters above ground air temperatures in shade while LST is a measurement of thermal radiation emitted from the land surface. In addition, MODIS passes the study site once per day while stations are capturing fine-scale dynamics of air temperature. A more complex model taking into account diurnal cycles can potentially improve the relationship between station temperatures (min, max, average) and MODIS remote sensing LST.

Universal Kriging Average Annual TMAX: Predictions

Universal Kriging Average Annual TMAX: Std Errors

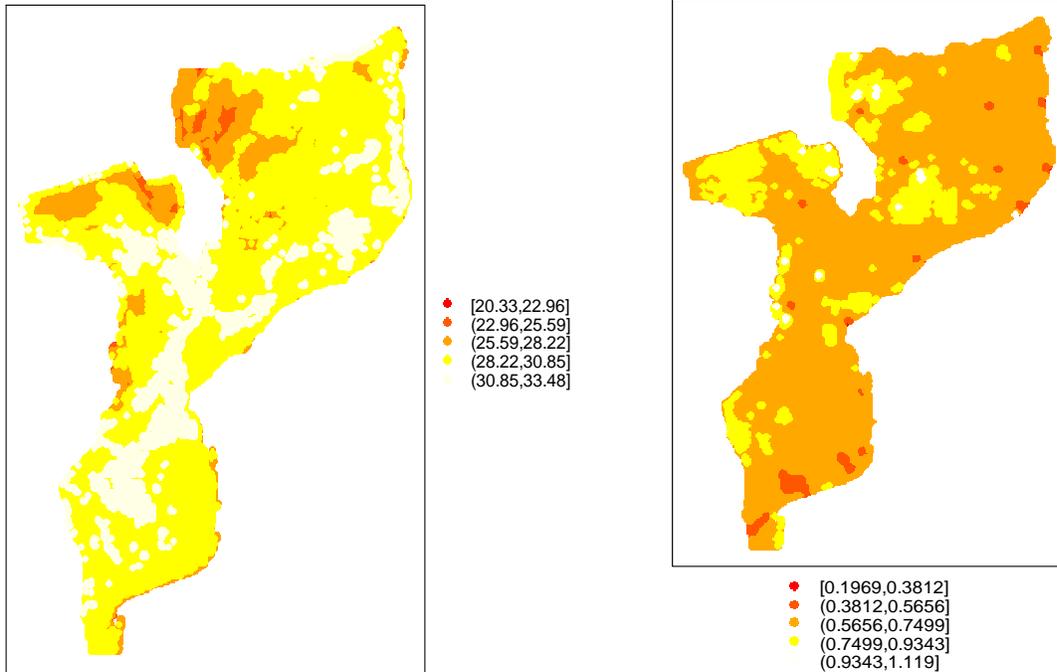


Figure 9: UK shows a tighter fit compared to the MODIS LST for predicting station observations; however, the spatial distribution of land surface temperature according to the kriging method is poor as can be seen in the predictions and standard errors. This is likely due to the sparsely populated station locations and lack of a comprehensive station network.

Table 9: LST predicted value distributions. MODIS LST tends to over estimate station data. Better estimates of predicting station observations were obtained through OK using only station data or by incorporating covariate data through UK. However, the poor spatial interpolation of the kriging methods highlights the advantages of the remote sensing inputs.

Summary of Predicted Values by Estimation Method							
Temperature Data	Estimator	Minimum	1 st Quartile	Median	Mean	3 rd Quartile	Maximum
Average Annual	MODIS LST	29.3	31.95	33.4	33.52	35	39.4
	OK	24.87	29.35	29.58	29.7	30.03	33.23
	UK	20.33	28.55	29.58	29.26	30.33	33.48
	Actual	24.6	29.05	29.9	29.76	30.6	33.5
DJF	MODIS LST	26.5	32.9	34.1	34.47	37.05	39.9
	OK	25.53	31.33	31.7	31.64	32.02	34.35
	UK	21.4	30.08	31.34	30.97	32.23	34.59
	Actual	25.2	31.35	31.8	31.77	32.7	34.6
MAM	MODIS LST	25.1	29.2	30.2	30.54	31.6	37
	OK	25.48	29.35	29.52	29.59	29.91	32.23
	UK	22.71	27.61	28.6	28.49	29.5	33.11
	Actual	24.2	29.3	29.8	29.71	30.5	33.2
JJA	MODIS LST	25.6	28.15	30.5	30.06	31.65	37
	OK	24.94	26.33	26.75	26.88	27.54	28.39
	UK	18.8	25.31	26.33	26.09	27.13	31.63
	Actual	22	26	26.9	26.95	28.1	30.3
SON	MODIS LST	32.4	36.05	37	38.47	41.1	45.5
	OK	27.43	29.87	30.88	30.77	31.52	35.76
	UK	21.84	30.28	31.82	31.52	32.97	37.41
	Actual	27	29.5	30.5	30.68	31.65	36.3

Table 10a. RMSE for Tmax. Universal kriging provided the lowest RMSEs for all temperature data sets. The MODIS LST data consistently overestimated TMAX station observations, resulting in relatively large RMSEs.

Root Mean Squared Errors (RMSEs)			
Tmax			
	MODIS	Ordinary	Universal
Temperature Data	LST	Kriging	Kriging
Average Annual	4.111067	1.841763	0.9966281
DJF	3.476005	2.035451	0.9536262
MAM	1.742063	1.967962	1.2268291
JJA	3.601147	1.764987	1.0627068
SON	8.184317	1.997847	1.1528188

Table 10b. RMSE for Tmean¹.

Root Mean Squared Errors (RMSEs)			
$(T_{max} + T_{min}) / 2$			
	MODIS	Ordinary	Universal
Temperature Data	LST	Kriging	Kriging
Average Annual	9.300561	1.831314	1.1303305
DJF	7.776721	1.925731	0.7262684
MAM	6.224112	1.990822	1.0423221
JJA	9.205551	1.869054	1.2913091
SON	13.731509	1.712752	1.234692

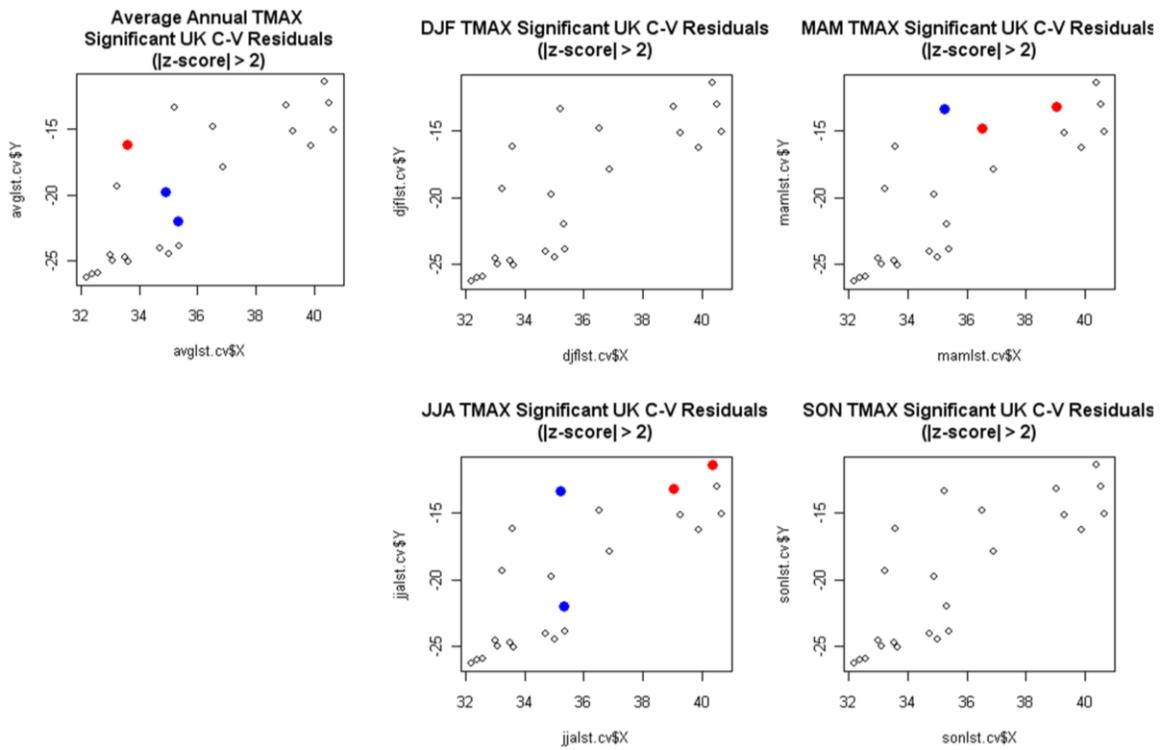


Figure 10: Tmax residuals for average annual and seasonal UK predictions.

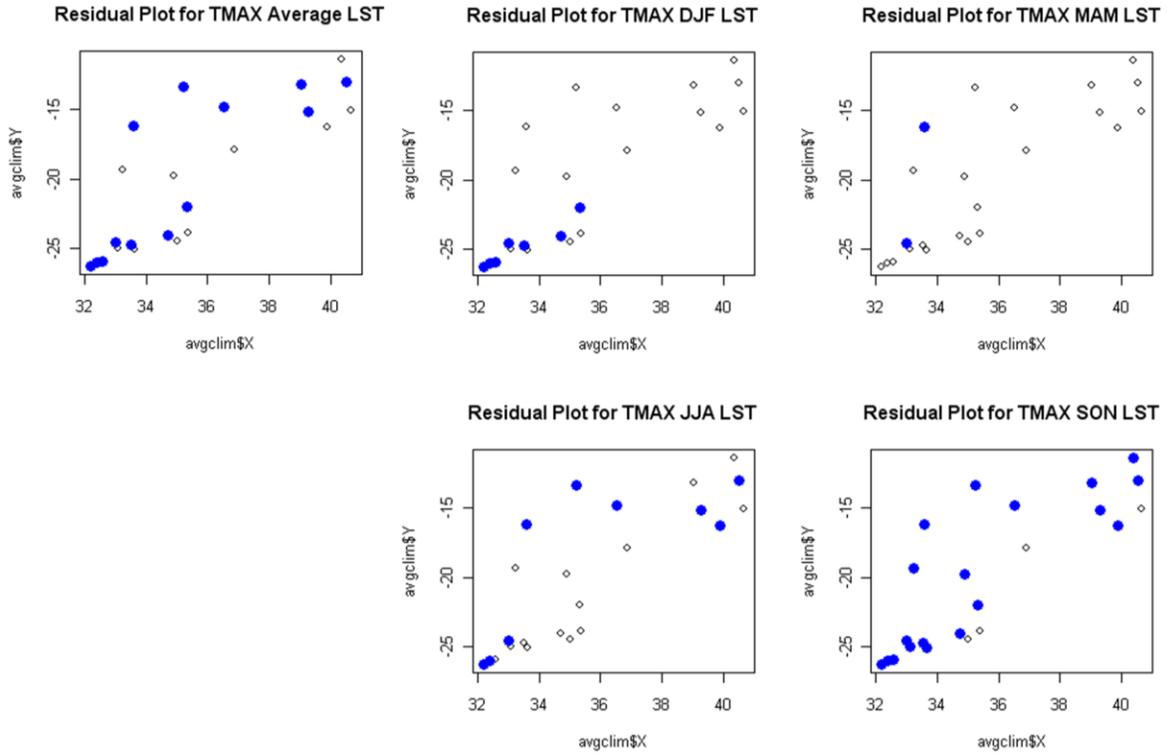


Figure 11: Tmax residuals for LST.

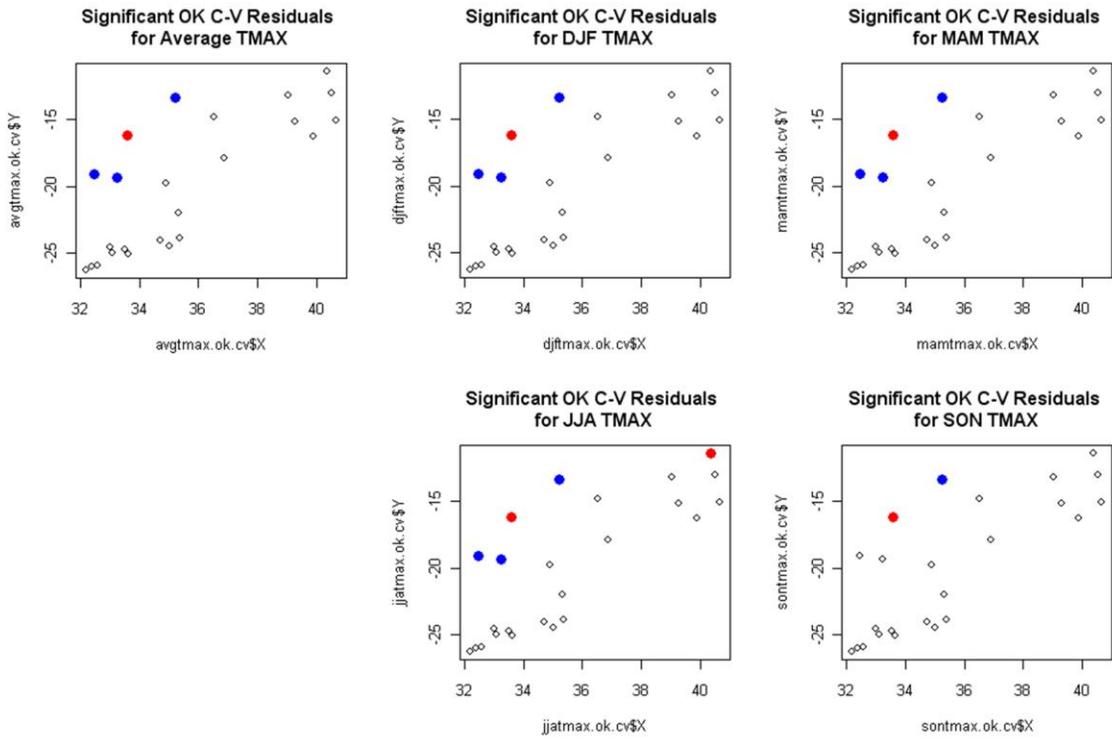


Figure 12: Residuals for OK of Tmax.

Zonal Mapping

The zonal mapping relied on the available input parameters to delineate homogenous weather zones and agroclimate zones for Mozambique. A suite of zonal products were generated using climate and agricultural spatiotemporal information. Variables were primarily derived from the remotely sensed weather information (i.e., TRMM PPT & MODIS LST), soils, and topographic modeling. Task 1 summarized the TRMM PPT and MODIS LST remotely sensed weather information. Below are brief summaries for the A.) soils and B.) topographic input variables used for zonal mapping:

A.) Soils

To integrate soils information into the zonal mapping and to parameterize the crop model the Harmonized World Soil Database (FAO 2009) was utilized. This soils database was developed by multiple institutions including FAO, International Institute for Applied Systems Analysis (IIASA), among others. Spatial soil information was extracted and gridded to identical modeling units as the remotely sensed cells. The soil spatial parameters used for zoning included the following:

1. Gravel content (% volume)
2. Sand fraction (% weight)
3. Silt fraction (%weight)
4. Clay fraction (% weight)
5. Bulk density (kg/dm³)
6. Organic carbon (% weight)
7. pH (-log*H⁺)
8. Cation exchange capacity (cmol/kg)
9. Base saturation (%)
10. Total exchangeable bases (cmol/kg)
11. Calcium carbonate (% weight)
12. Gypsum (% weight)
13. Sodicity (%)
14. Salinity (dS/m)

B.) Topography

Topographic information was obtained from the NASA Shuttle Radar Topography Mission (SRTM: Jarvis et al., 2008). This project focused on the use of void filled version-4 resampled to 90m resolution for a wall-to-wall Digital Elevation Model (DEM). SRTM are available in 5x5 degree tiles in geotiff from Consultative Group on International Agricultural Research (CGAIR) Consortium for Spatial Information. Many papers detail the accuracies, scales, and input imagery for the SRTM DEM. As input into the zonal mapping procedures we generated a suite of topographic indices that were scaled to the identical modeling units for further analyses. The topographic indices used as input into zonal mapping included the following indices:

1. Elevation
2. Slope
3. Aspect

4. Profile Convexity
5. Plan Convexity
6. Longitudinal Convexity
7. Cross Sectional Convexity
8. Minimum Curvature
9. Maximum Curvature
10. $p = \cos(\alpha) \sin(\theta)$
11. $q = \sin(\alpha) \sin(\theta)$

where α is the angle of aspect in degrees and θ is the angle of the slope in degrees. The values of p and q represent aspect scaled by the steepness of the slope. That is, these values are largest in magnitude on the steepest slopes and approach zero in flat areas.

Zonal Mapping Analyses

A set of hierarchical zonal maps were generated to identify homogenous climate zones and identify agroclimate zones. The zonal mapping procedure used Principal Components Analysis (PCA) as a method to reduce data dimensionality and extract unique maximum information. PCA is a well-established technique in which original data is transformed into a new coordinate system, which acts to condense the information found in the original inter-correlated variables into a few uncorrelated variables, called principal components. With respect to agroclimate and biogeophysical data, PCA transforms large data sets into relatively few meaningful uncorrelated orthogonal variables/dimensions (i.e., the principal components) that represent most of the information present in the original spatial data. In any principal components rotation, the first component or dimension accounts for the maximum proportion of the variance of the original input, and subsequent components account for maximum proportion of the remaining variance. To integrate the PCA factor scores (or components), K-means clustering was applied with partial F-tests to determine the number of cluster classes.

The summary procedures for the zonal mapping of homogenous climate zones were:

1. Ran PCA for 10 yr average annual, DJF, MAM, JJA, and SON climate variables with elevation derivatives.
2. Identified 5 components for each. Component definitions varied by season.
3. Ran K-means clustering algorithm on selected subset of components for annual and each season.
4. Mapped cluster identifications for each.

The summary procedures for the zonal mapping of homogenous agroclimate zones were:

1. Ran PCA for soil variables only and identified 3 components.
2. Ran PCA for climate and soil variables together, using only those soil variables that loaded with the 3 components identified above.
3. Ran K-means clustering algorithm on two subsets of components: 1234 and 1245.
5. Mapped cluster identifications for both.

To smooth out the agroclimatic maps we ran a generalization scheme by applying a majority filter and small pixel grouping sieve filter.

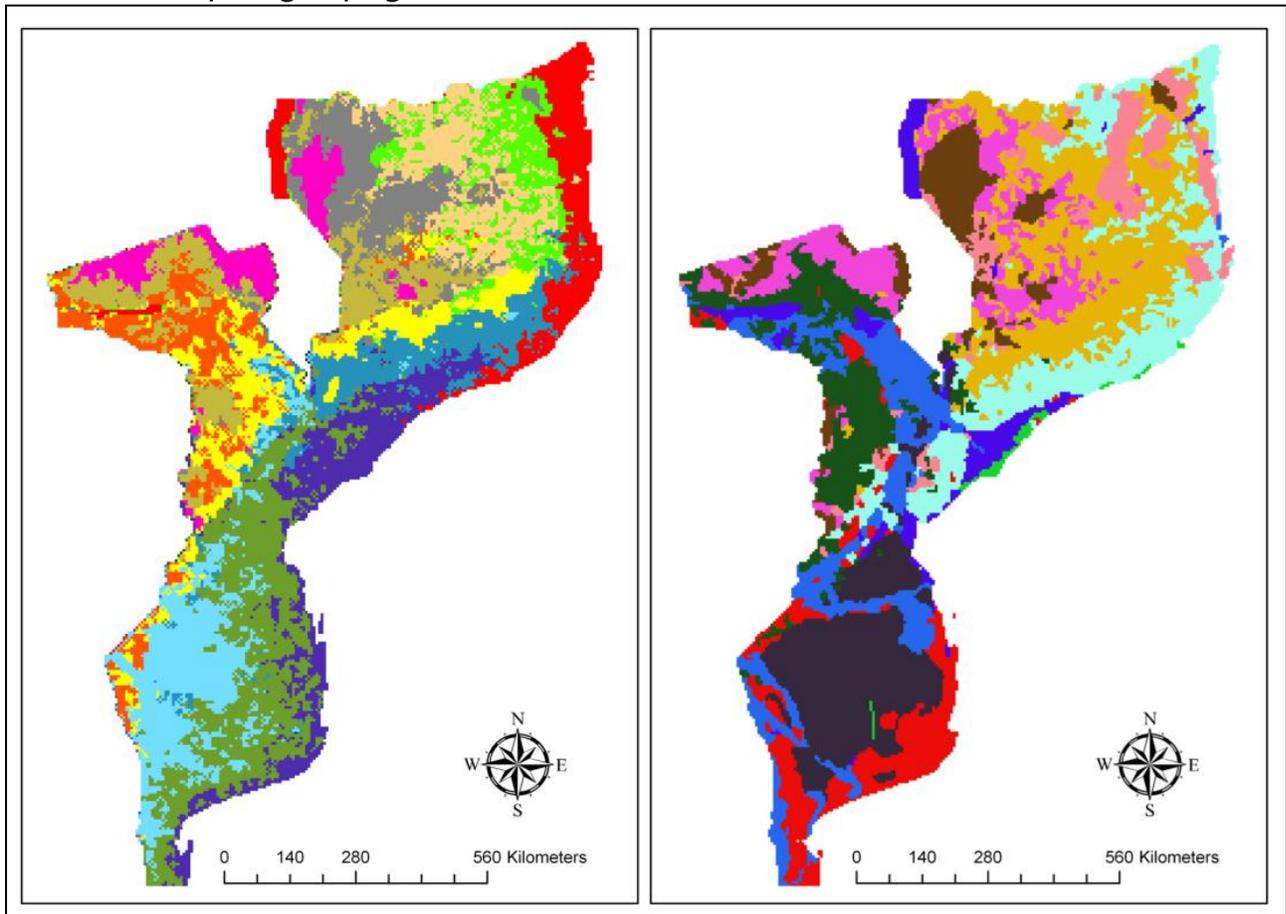


Figure 13. Final map product (above left) for homogenous weather zones for Mozambique utilizing ten year monthly average satellite remote sensing weather inputs and geostatistical methodologies. Final map product illustrated for agroclimate clusters map product (right) were designed in a hierarchical (scaled) approach with 375 individual zones and 11 major agroclimate clusters that are statistically unique.

The homogenous weather maps and the agroclimate maps have similarity and differences and should be used according to specific application. The PCA analysis found that elevation, rainfall and location, p and q, and temperature were the most statistically important variables used to determine the homogenous weather regions by explaining 35%, 23%, 12%, and 11% of the variation in the component loadings. The PCA factors across seasons were similar except for LST becoming more influential in the drier periods although elevation was always the dominating factor. As expected, the elevation gradients can be seen in both the weather and agroclimate zonal map products, which was shown in the PCA results to be a driver of zones. Soil composition, soil moisture attributes, and soil conductivity/mobility were the major component loadings for the soil dataset. The drier seasonal climate has some influence on the agroclimate zonal maps as seen by the representation of southern features in Gaza and Inhambane relative to the weather zonal

map with a stronger coastal factor present likely influenced by the Inter Tropical Convergence Zone and Indian Ocean temperatures. The final zonal map products were smoothed using a generalization majority filter. The maps were generated in a hierarchical fashion with 375 individual zones and 11 major agroclimate clusters that are statistically unique. To simplify and provide general details and short, interpretive titles were provided in table 11.

Table 11. Major agroclimate clusters names identified from bioclimatic and agricultural factors.

Cluster #	Descriptive Name
1	Dry hot semiarid southern lowlands
2	Tropical central coast with dry periods
3	Dry seasonally hot southlands
4	Semi-tropical wet season with dry periods
5	Tropical wet coastal and wet north-central lowlands
6	Northern mid-elevations with cooler rain season
7	West-central mid-elevation with cooler wet season
8	Seasonal valley regions
9	Semi-tropical wet highlands
10	Northern moist cool season
11	High elevation with cooler tropical wet

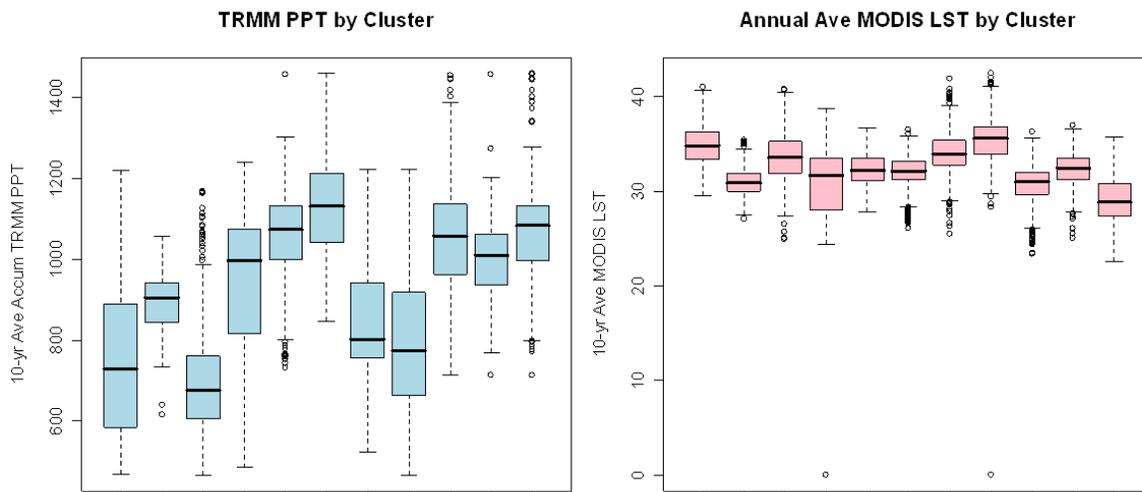


Figure 14a. Annual accumulated TRMM PPT and annual average MODIS LST by cluster between 2002-2010.

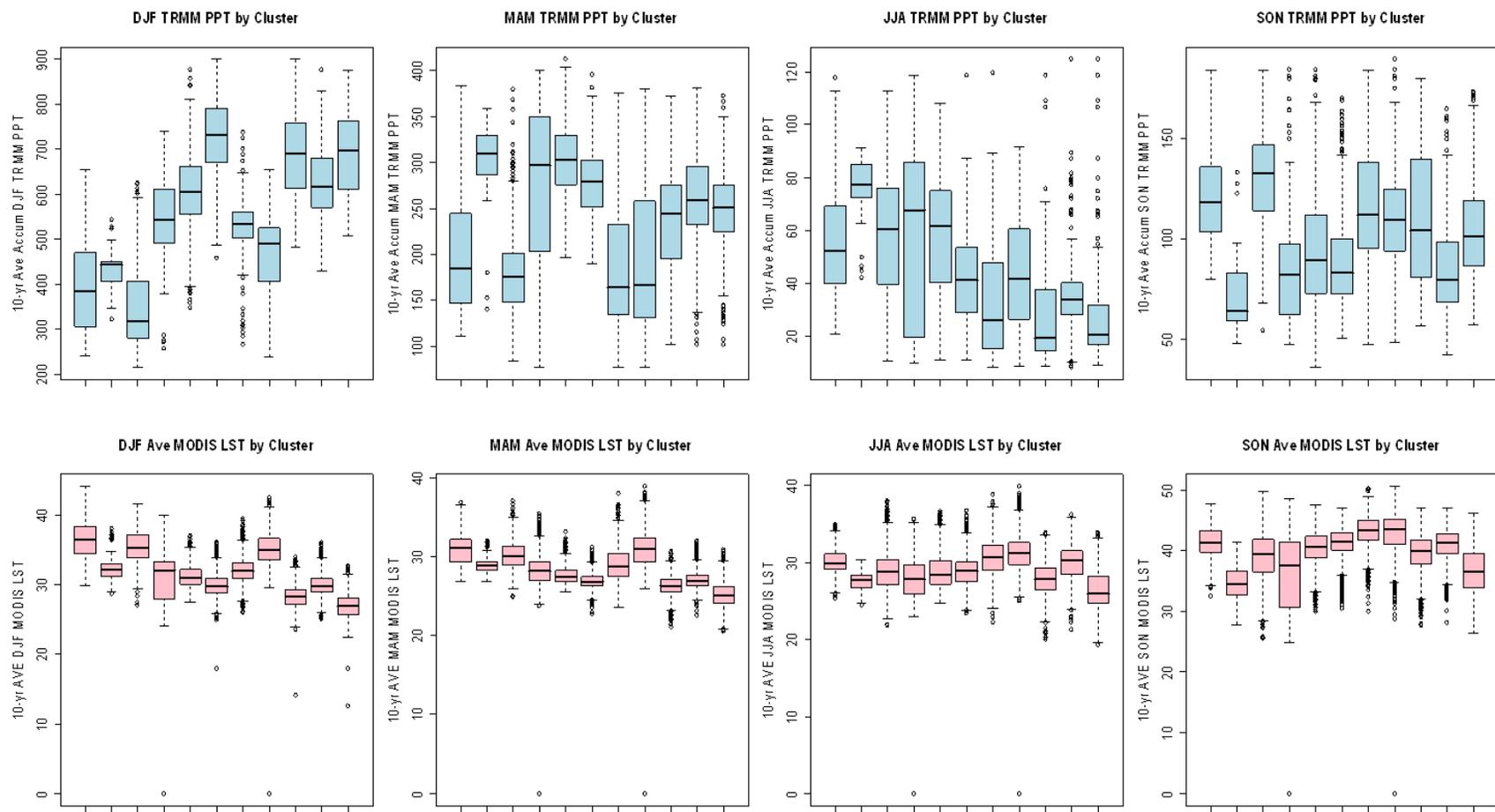


Fig 14b. Box and whisker plots for seasonal TRMM PPT total accumulated averages by cluster and seasonal MODIS LST averages by cluster between 2002-2010. These clusters and seasonal weather averages further quantify the descriptive names assigned to each cluster and can be used for further analysis of agroclimate clusters. Note scales (y-axis) are not equal across seasons.

Objective 1 Conclusions

- Weather station observations generally showed satellite measurements of rainfall to be accurate over space (geography) and time (seasons) with strong correlations
 - Weather station observations generally showed satellite measurements of temperature correlated moderately with a tendency to overestimate station locations likely due to the differences between data recording (air temperature vs. land surface temperature)
 - Remote sensing measurements show detailed spatial and temporal patterns not available from station observations alone and not interpolated strongly by the geostatistical kriging methodologies
 - Elevation, rainfall, location, and temperature were the most statistically important variables used to determine the homogenous weather regions
 - Soil composition, elevation metrics, soil moisture attributes, climate location, and soil conductivity were the most statistically important variables within the bioclimatic datasets
 - The final map products were designed in a hierarchical (scaled) approach with 375 individual zones and 11 major agroclimate clusters that are statistically unique
 - Maps were created at the 5km spatial resolution / scale
 - The agrocluster maps contain more detail than current available maps that simply group regions by coarse weather products, political boundaries, or interpretation; the agrocluster maps use several key scientific inputs to determine similar regions and the approach is methodologically automated, scalable and operational
-

Task 2: Crop suitability

In preparation for quantitative analyses of crop susceptibility to climate variability and drought, crop suitability was modeled across Mozambique using the DeNitrification-DeComposition agro-ecological model (DNDC). Suitability was modeled and mapped for all major crops including: beans, cassava, cotton, groundnut, maize, millet, potato, paddy rice, rainfed rice, sorghum, and tobacco.

A process-based agricultural productivity model was utilized to generate crop yield distributions and develop crop suitability index maps. The Denitrification-Decomposition (DNDC) model (Li et al., 1992, Li et al., 2006) is a process-based computer simulation model focusing on the exchanges of water, carbon (C) and nitrogen (N) between terrestrial ecosystems and the atmosphere. DNDC can be freely downloaded at <http://www.dndc.sr.unh.edu/>. DNDC works at the molecular or microorganism level driven by thermodynamic and reaction kinetic principles. DNDC has been widely tested at multiple scales with accurate results. Thus, DNDC is a good tool for high-resolution and/or regional studies such as the district or zonal level and scaled to national levels for inventory or risk programs. DNDC requires a suite of input parameters and predicts yield, water, C, and N exchanges between the atmosphere and the plant-soil systems at a daily time step.

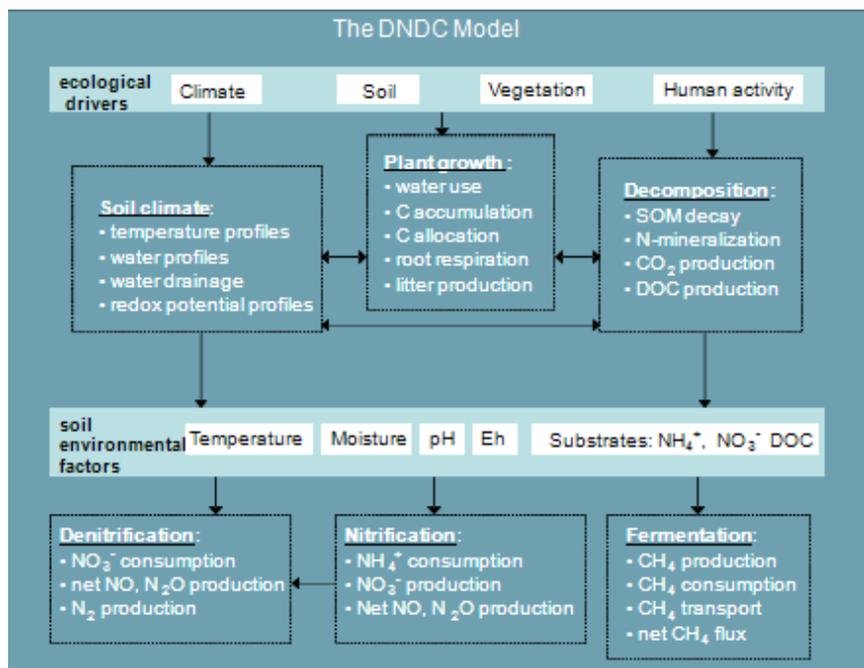


Figure 15. Engineering framework and input categories for DNDC to generate yield.

The DNDC model was originally developed to simulate the effects of major farming practices (e.g., crop rotation, tillage, fertilization, manure amendment, irrigation, flooding, weeding, grass cutting and grazing) and climate change (temperature and precipitation) on yield and C and N cycles in various ecosystems. By tracking vegetation biomass production and decomposition rates, DNDC also simulates long-term soil organic carbon (SOC) dynamics,

predicts methane (CH₄), nitrous oxide (N₂O), and greenhouse gas (GHG) emissions by tracking the reaction kinetics of nitrification, denitrification and fermentation across climatic zones, soil types, and management regimes (Li et al. 2002). The simulated vegetation growth can be used to generate yield distributions, suitability indices, and assess climate scenarios.

We developed a Crop Suitability Index (CSI) for Mozambique by using DNDC to understand agricultural risks from weather fluctuations and climate change. We modeled crop suitability by agroclimate zone and scaled up to the cluster within Mozambique via DNDC crop yield modeling results. For each crop of concern, to answer the question “how well does this crop perform, on average, within this zone and within this cluster?” we assumed a wall-to-wall distribution of crops in that respective modeling unit and ran DNDC using 2010 climate data. Best available data was used as crop map layers (i.e., Ramankutty et al 2008, Monfreda et al 2008, Sacks et al 2010) . We ran DNDC in two modes: one using conventional fertilization (i.e. best information on actual fertilizer N applications) and one using “optimal” fertilization (i.e. fertilizer N is applied whenever soil N falls below crop demand). The first mode addresses the likely situation that crops are farmed using standard (and typically low in Mozambique) N inputs. The second mode sidesteps the vexing question of whether suitability is actually related to underlying geography or low N inputs, and facilitates interpretation of other important variables (e.g. soil texture or annual precipitation).

Table 12. DNDC crop model input parameterization for generating crop suitability index.

Input parameters		Output parameters	
Climate	- Daily max and min air temperature - Precipitation - Solar radiation - Atmospheric N deposition	Crop Scheme	- Photosynthesis - Respiration - Water demand and transpiration - N demands/uptake - C allocation - Yield and litter production
Soil	- Bulk density - Texture (clay fraction) - Organic C content	Soil	- Temperature profile - Moisture profile - pH profile - Eh profile - Evaporation - Water leaching and runoff - SOC dynamics - N leaching - Emissions of N ₂ O, NO, N ₂ , NH ₃ , CH ₄ and CO ₂
Human Activities or Managements	- pH - Tillage - Irrigation - Runoff/Fertilization - Manure amendment - Grass cutting		

Cropping calendar was based on expert knowledge and FAO Crop Calendar input <http://www.fao.org/agriculture/seed/cropcalendar/>. For crop systems with information in the FAO Crop Calendar, we followed these general rules:

- For single rotation crop systems, in order of preference:
 - Use mean plant date / end harvest date (to allow for full growing season)
 - Use mean plant date / longest cropping cycle (to allow for full growing season)
- For double rotation crop systems:
 - Use earliest possible plant date and longest possible cropping cycle to ensure that 2nd planting is during the key seasonal period
- For crop systems with no information in the FAO Crop Calendar, we used plant/harvest dates from the DNDC database (which, for each crop, were uniform across Mozambique) and adjusted for the Mozambique rainy season (October – December timeframe, depending on cropping cycle)
- Single cassava rotation was the only exception to the above because of the extremely long cropping cycle (minimum 1 year) – we set an early plant date and allowed the crop to mature for a single year to maximize yield potential

For soil inputs we used the Harmonized World Soils Database (HWSD). For each unit in the modeling scheme the area-weighted mean value was calculated for four soil attributes: clay fraction (% of weight - a proxy for soil texture), bulk density (g/cm^3), pH, and organic matter content (% of weight). Nitrogen deposition data were based on the values in the original DNDC embedded grid. For 2010 climate data we relied on daily meteorological data (maximum and minimum temperature in $^{\circ}\text{C}$ and precipitation in cm) derived from the NASA Modern Era Retrospective-Analysis for Research and Applications dataset (MERRA) (MERRA 2010, Rienecker et al 2009) to drive daily climate input requirements. MERRA reanalysis is considered among the best available and most current multidimensional climate data available. We qualitatively assessed MERRA using the TRMM and LST products and found MERRA to be satisfactory and acceptable for this analysis.

To express the results of this analysis we used a simple index to indicate how well a crop grows relative to “best” yield within Mozambique:

$$\text{yield}_{\text{cluster}} / \text{high yield}$$

where “high yield” is the 95th percentile of yield within Mozambique.

Selected maps of crop suitability index are shown below for all crops combined and the four top crops by area (top ~75% by area) along with bar charts (see appendix) indicating crop performance by cluster for the given run type.

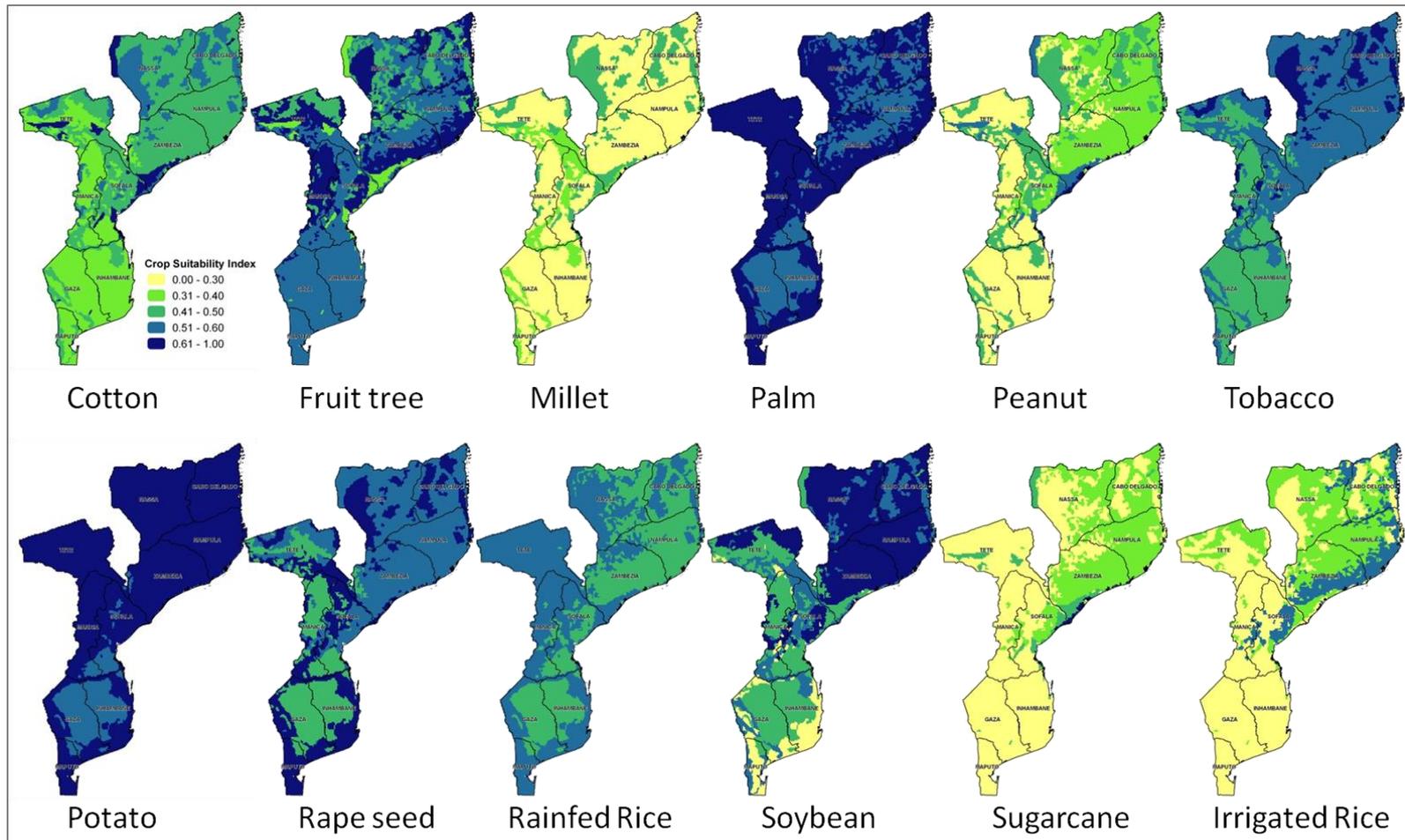


Figure 16a. Crop Suitability Index for selected food and cash crops with conventional fertilization shown and 2010 weather drivers. Millet and sugarcane tend to have relatively moderate to low suitability. Peanut, sugarcane, and irrigated rice have clusters in the north with higher suitability.

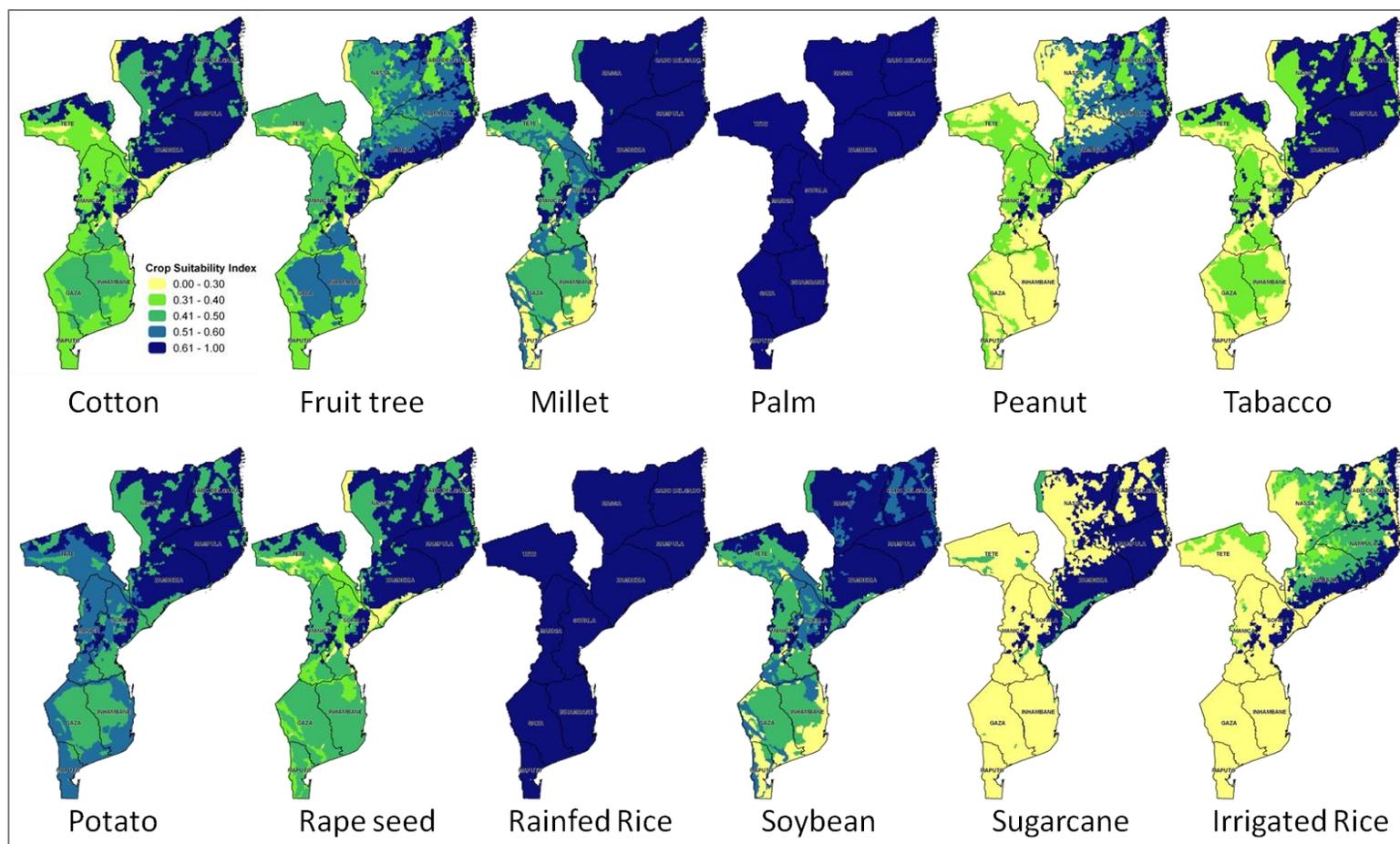


Figure 16b. Crop Suitability Index for selected food and cash crops with optimized fertilization shown and 2010 weather drivers. Rainfed rice and palm have nearly uniform and high CSI, which is likely a model parameterization issue that needs further characterizations with field calibration work. Similar northern and coastal clusters tend to have relatively higher suitability across all major cash and food crops.

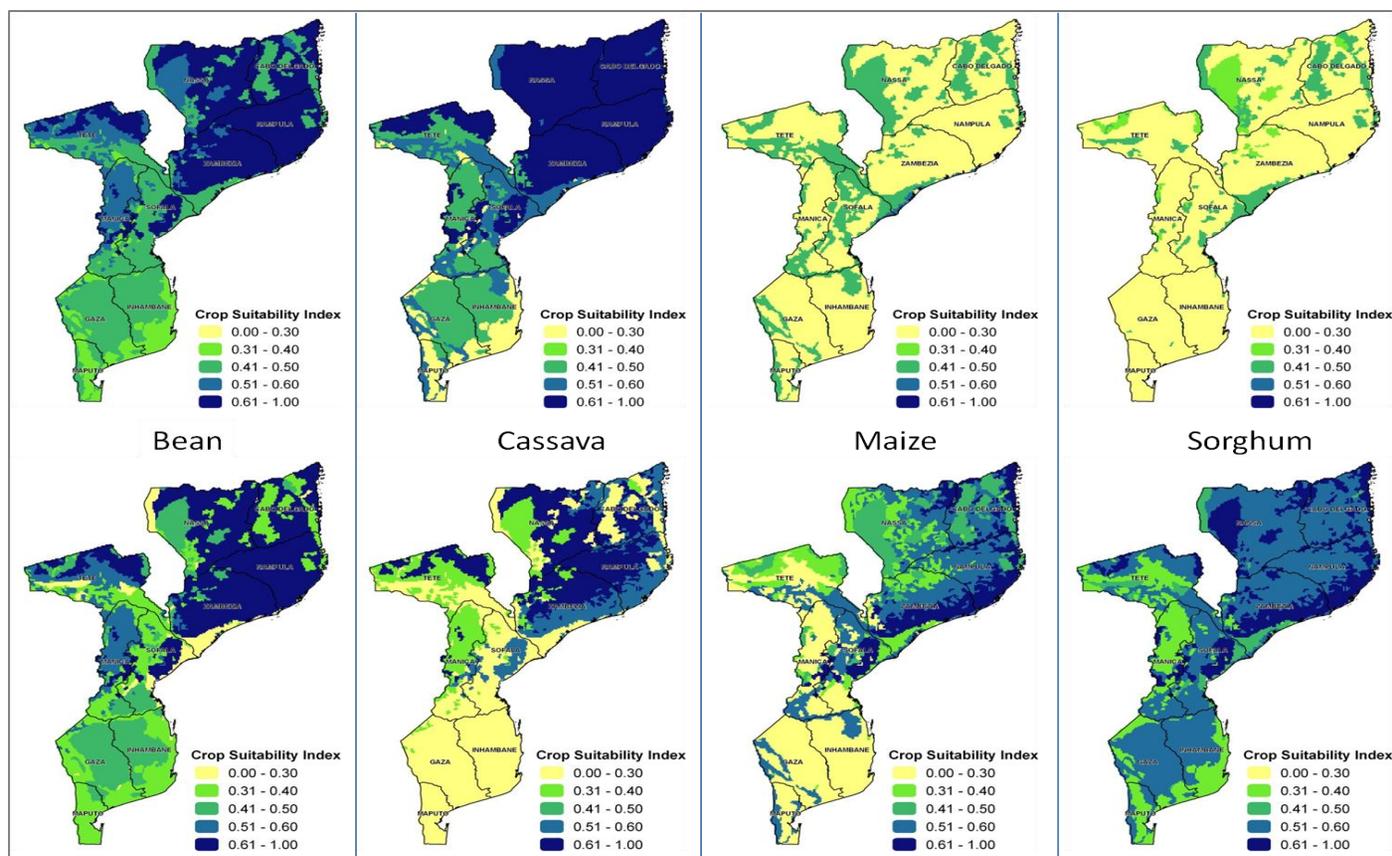


Figure 16c. Crop Suitability Index for major crops by area (top 75%) with conventional (top) and optimized (bottom) fertilization shown. Under conventional fertilization beans have relatively modest suitability across most clusters with higher suitability in northern clusters and west-central clusters and similar CSI for cassava although a greater range of suitability. Maize and sorghum have modest to low suitability across most clusters with patchy and isolated zones of moderate suitability. These are relative indices so comparisons between fertilization practices need be applied cautiously. For example, cassava shows relatively lower suitability in clusters 11 and 12 (annual averages of ~1050mm ppt, 28-32°C) along with provinces of Gaza, Inhambane and Maputo. This does not mean that yields are lower when compared to conventional fertilizer applications.

The selected suitability maps by top areal crop coverage shows ranging crop suitability based on crop type and agroclimate clusters. Yields and all data (for all crops) are also available within the GIS; however, the suitability indices provide a powerful tool to compare across crop types, management practices, and geography. In general CSI is higher in the northern and coastal properties. This pattern is highlighted in the figure for beans and cassava. These suitability maps generally agree with actual production and mean yields across Nampula and Zembezi and portions of Cabo Delgado, Niassa, and Tete. Beans tend to have a smaller range of suitability as indicated by the CSI maps when compared to cassava with similar high suitability regions but lower CSI in the south and coastal areas of Inhambane and Maputo. The increase in drought tolerant varieties of beans has improved the suitability of beans across Mozambique.

The CSI for maize and sorghum have very similar suitability based on the DNDC simulations with 2010 data inputs. The highest suitability categories tend to occur in patchy locations primarily in the central and northern regions of Mozambique. These maize patterns generally match agricultural census (TIA: 2005) information for Mozambique. Noted is the increase in suitability in the north and coastal regions with optimized fertilizations methods with the south remaining lower suited for maize.

It is noted that the crop suitability index is not production and does not imply that a location with “more optimal” or “higher” suitability delineates a location where high yields will automatically occur nor zones where high yields do occur in reality. Rather, this is a normalized map showing the relative mean difference from a highly suitable growing possibility (“higher”) and the relative mean difference for a given crop at a given location. “Other factors” (i.e., road networks, distance to market, conflicts, market price, inflation, management, adaptations, fertilizers, technology) will influence cropping suitability decisions and ultimate suitability. In Mozambique most farmers do not achieve optimal yields due to a variety of factors (AFTS, Report # 32416-MZ 2006, Coughlin 2006, Loening and Perumalpillai-Essex 2005, INGC 2009, PEDSA 2010). The crop suitability map that was generated is a relative quantitative index to provide guidance on relative yields based on agroclimate conditions with all “other factors” being equal.

Objective 2 Conclusions

- Results show locations of “lowest” Crop Suitability Index are dispersed throughout agroclimate clusters in Gaza, Inhambane, Maputo and southern portions of Sofala and Manica
- Crop Suitability Index for the top four crops by area (75%) was found to have:
- Beans perform modestly in the south to relatively high in the north
- Cassava moderate to high in the north and northern coastal clusters
- Maize was generally low with patchy and isolated moderate suitability
- Sorghum was generally the lowest of the four top crops by area with a few patchy clusters of moderate suitability in Sofala, Cabo Delgado, Niassa, Nampula, and Tete
- Few crops or locations have extremely high crop suitability relative to global averages due to the current farming practices and lack of optimal inputs; improved

inputs (fertilizer) shows what locations and what crops increase crop suitability and resiliency- for example, maize in northern coastal clusters

- Improved geospatial information on farming practices and crop calendar might improve model precision

Task 3: Crop Vulnerability

Crop vulnerability and risk to weather was assessed at the agroclimate zone scale in Mozambique using yield from the crop model. Other vulnerabilities were also run and stored in a GIS. We simulated three strategic scenarios based on generally accepted climate projections from dynamic and downscaled models, the geostatistical relationships constructed in this project between temperature and precipitation, and historical and current trends in Mozambique and the region. This approach integrates the strengths of models, expert knowledge, and current findings. The scenarios include:

Table 13. Climate scenarios for crop vulnerability assessment.

Scenario	Annual Temperature (°C)	Annual Precipitation
Baseline	no change	no change
1	+1	-5%
2	+2.5	-10%
3	+5	-15%

The crop model was run in both conventional and optimized fertilization (where fertilizer N is applied when available soil N drops below crop demand) modes. To express the results of this analysis we created a simple vulnerability index which indicates each crop's performance relative to 2010 baseline within each agroclimate cluster:

$$100 * \text{mean rate}_{ij} / \text{mean baseline rate}$$

where i is the climate scenario and j is the fertilization mode.

Table 14. Vulnerability of All Crops to Climate Change by Agro-ecological Cluster

	Conventional Fertilization				Optimal Fertilization			
	2010 Climate	+1°/-5%ppt	+2.5°C/-10%ppt	+5°C/-15%ppt	2010 Climate	+1°/-5%ppt	+2.5°C/-10%ppt	+5°C/-15%ppt
cluster 1	100%	84%	84%	93%	100%	82%	84%	105%
cluster 2	100%	92%	90%	84%	100%	92%	91%	92%
cluster 4	100%	98%	94%	91%	100%	97%	88%	78%
cluster 5	100%	96%	90%	85%	100%	97%	93%	91%
cluster 6	100%	96%	89%	83%	100%	90%	79%	71%
cluster 7	100%	107%	104%	100%	100%	105%	97%	92%
cluster 8	100%	128%	127%	135%	100%	122%	125%	134%
cluster 9	100%	100%	93%	83%	100%	103%	93%	86%
cluster 10	100%	107%	135%	160%	100%	105%	131%	159%
cluster 11	100%	99%	89%	82%	100%	100%	92%	86%
cluster 12	100%	97%	106%	98%	100%	98%	112%	107%

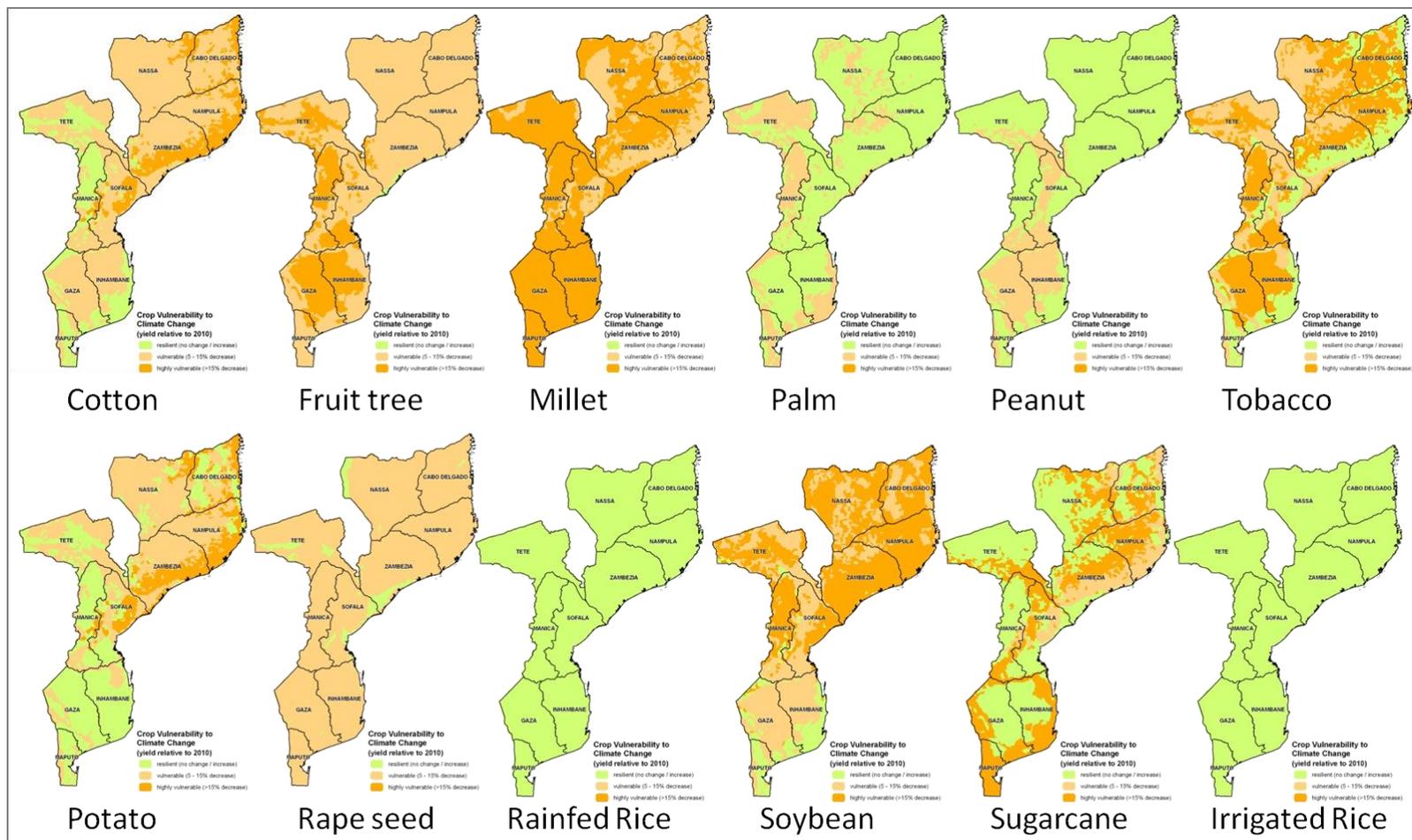


Figure 17. Crop Vulnerability Index (CVI) for selected food and cash crops with conventional fertilization and climate scenario 2 (+2.5°C and -10% total ppt) shown compared to 2010 weather drivers and yield baselines. Millet, tobacco, soybean, sugarcane, and fruit tree have the largest area of increase in relatively higher vulnerability.

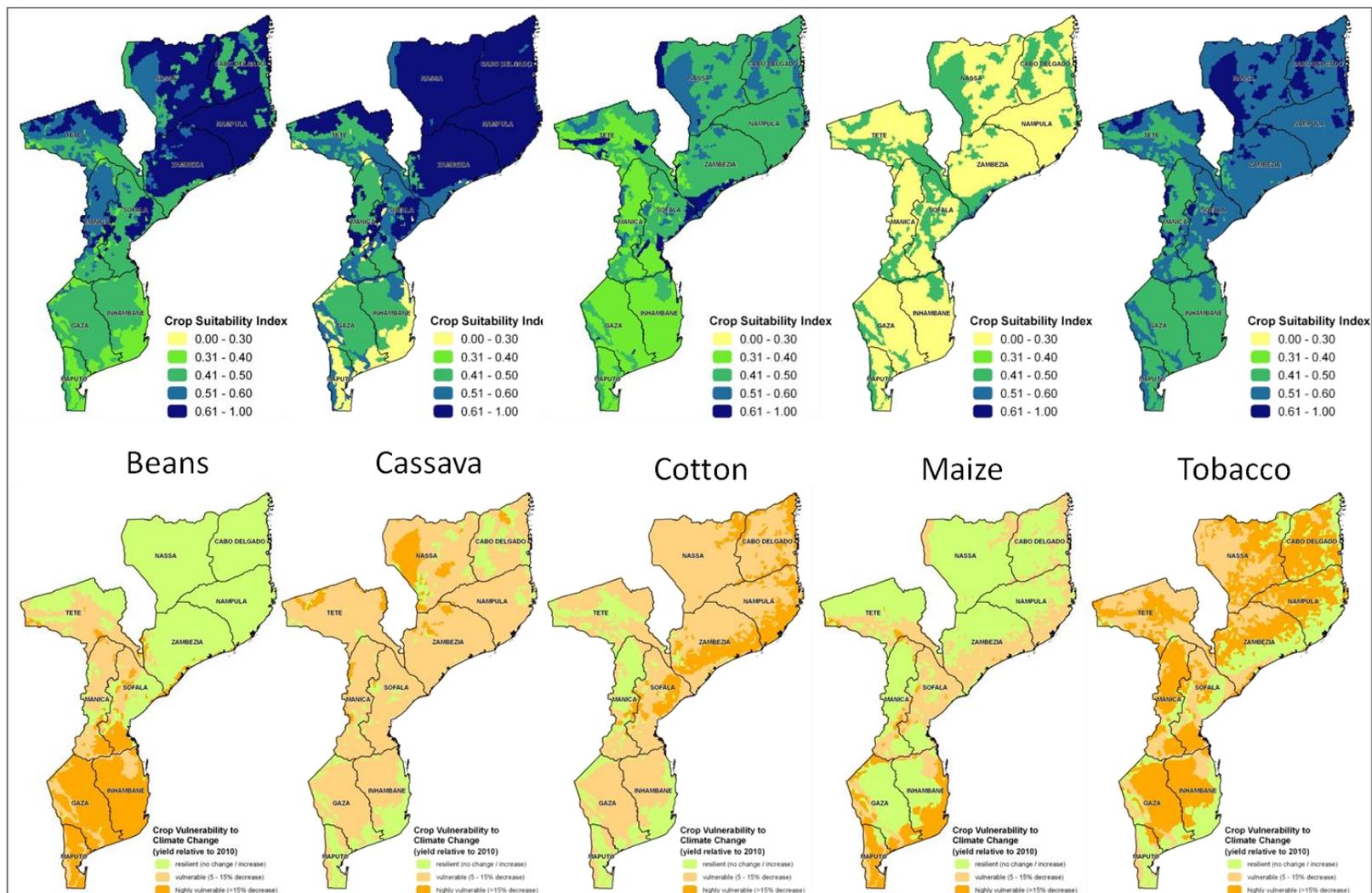


Figure 18. CVI (bottom) for climate scenario 2 (+2.5°C and -10% total ppt) and CSI (top) under conventional fertilizer for key crops in Mozambique compared to 2010 weather drivers and yield baselines. Spatial comparisons show relatively high suitability cotton clusters become highly vulnerable. Tobacco tends to have substantial area become highly vulnerable throughout Mozambique.

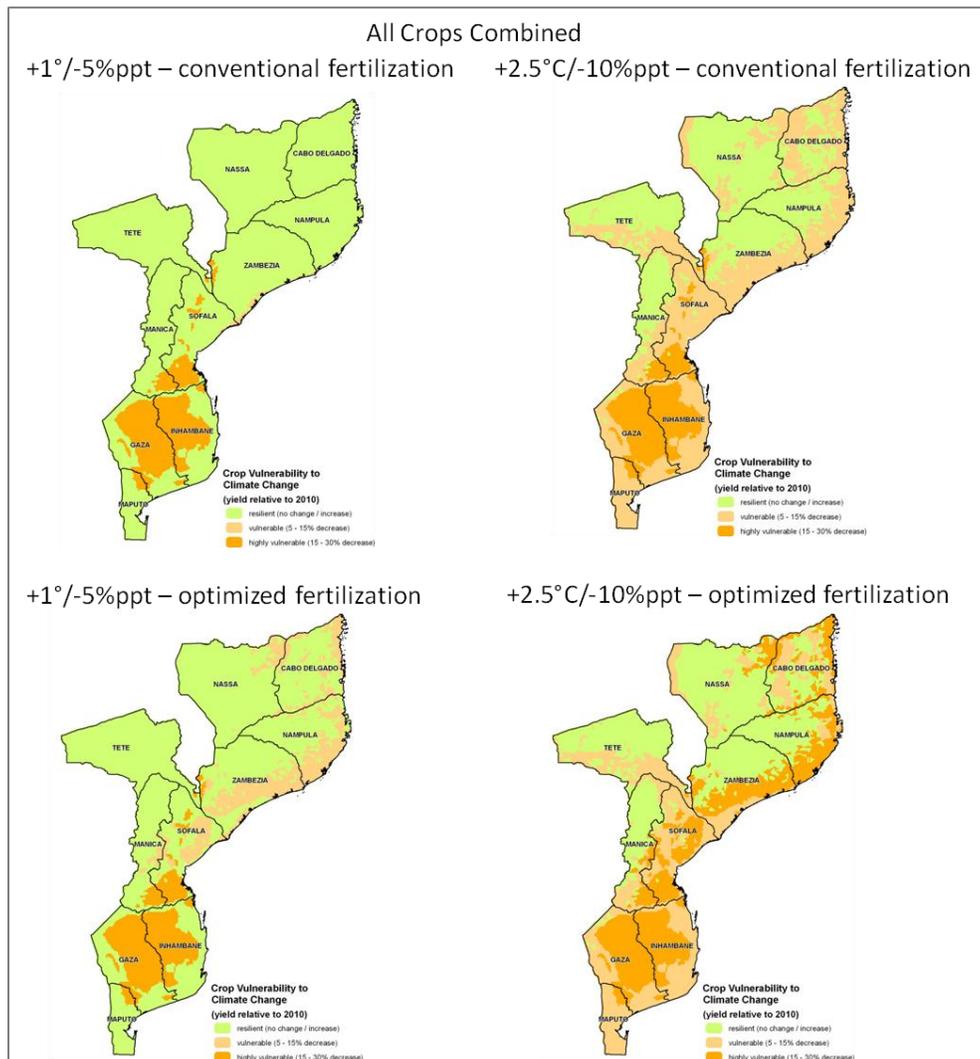


Figure 19. All crops combined for the scenario 1 (left) and 2 (right) are highlighted for conventional (top) and optimized (bottom) CVI. In general clusters in the south and coastal regions are most susceptible to becoming highly vulnerable with warming temperatures and decreases in rainfall.

The vulnerability maps indicate that, in general, clusters the south-central region of Mozambique and covering large regions of Gaza and Inhambane, are highly vulnerable with 15-30% reductions in yield compared to baselines. In the most extreme scenario these same clusters show less vulnerability due to the complexity of the processes that are occurring. In addition, these areas have a relatively small amount of crop area and not much absolute change however some relative change thus causing an artifact in the map result.

With an increase of 2.5 degrees in temperature, a reduction of 10% in total rainfall, and using conventional fertilization the agroclimate zones along the coast and central Mozambique have a decrease of 5 to 15% in yield compared to baseline yields and become

vulnerable. This represents a large sector of the agricultural industry in Mozambique. In the optimized fertilization scenarios the coastal agroclimate clusters and south-central clusters become highly vulnerable with an increase of 2.5°C and a 10% reduction in precipitation compared to the 2010 baseline. This does not imply that the optimized yields are lower than the conventional yields for the same climate scenario; rather, that yields are lower compared to the relative baseline and in fact the highly vulnerable optimized fertilizations yields are typically higher than the conventional fertilizations yields for the same zone.

These indices were created with DNDC which is a process based, or mechanistic, soil biogeochemical model that simulates C and N cycling based on soil conditions, daily weather and agricultural management (fertilizer use, irrigation, tillage, etc). The power of a modeling tool like DNDC for assessing crop vulnerability to weather variability lies in its ability to integrate weather drivers (e.g. precipitation and temperature) with soil conditions and management practices to assess crop growth conditions based on soil N availability, soil moisture and growing degree days. The role of a process model like DNDC in the assessment of crop vulnerability to weather variability is to capture the interactions between conditions for crop growth and weather, which is shown in the suitability and vulnerability indices. These interactions are complex and typically not linear. For example, in regions where precipitation can be limiting to crop productivity, one could imagine that an increase in precipitation would lead to improved growing conditions. While this is generally correct, management practices will likely need to be adapted to the shift in precipitation in order to reduce crop risk. While increases in precipitation may improve soil moisture conditions for crop growth, shifts in precipitation can also impact availability of nitrogen for plant growth by altering nitrogen leaching and runoff and gaseous losses and immobilization through increased microbial use and nitrification and denitrification. However, shifts in management practices (e.g. timing of N fertilizer application) can reduce the risk of these confounding impacts of environmental drivers. Process models, like DNDC, can capture these effects. Therefore, interpretation of the DNDC results needs to be carefully carried out and the indices make this process easier.

Objective 3 Conclusions

- Results have been aggregated into a simple vulnerability index that represents crop performance relative to 2010 baseline within each agroclimate cluster
- Highly vulnerable (15-50% decrease in yield) regions include the south (Gaza, Inhambane, southern Manica & southern Sofala) with conventional farming practices
- Coastal regions become vulnerable with slight reductions in precipitation, timing, or intensity of precipitation; coastal regions become highly vulnerable with temperature increase of 5°C and decrease in total accumulated rainfall of 15%; this scenario is plausible according to current projections, recent trends, and the relationships we have established between temperature and precipitation in the study
- Some model complexities are highlighted with a few large zones within agroclimate clusters showing shifting yields with extreme scenarios relative to modest vulnerability and less extreme scenarios; this is related to the biogeochemical processes controlling stressors and can be improved with additional cal/val efforts
- The optimized fertilization should not be compared against the conventional fertilizer as these are not appropriate comparisons

Task 4: Field Validation

To carry out field validation and integrate local expert knowledge, AGS partnered with the International Livestock Research Institute (ILRI) to coordinate an in-country ground campaign. A set of questionnaires and field protocol to assess the modelling results and integrate local expertise was executed. Surveys were developed in English and translated into Portuguese. Translation was done by an experienced expert with a background in agricultural economics. The questionnaires were administered in Portuguese by an agricultural expert with wide professional experience from the ministry of agriculture and National Institute for Agriculture Research (IIAM). On a few occasions, the questions were further translated into local language which was mostly achieved by community extension officers. It is notable that continuous monitoring of crop productivity and related weather variability by agricultural institutions at provincial, district and village level also informed this analysis. Three sets of questionnaires, designed according to the needs and speciality of the audience were used to capture information on crops. These included 1) farmer's questionnaire, 2) key informant / expert questionnaire, and 3) focused group discussion questionnaire.

On the ground surveys were conducted in five districts and four Provinces namely: Chibuto, Gaza; Mabote and Homoine, Inhambane; Machanga, Sofala; and Nampula of Nampula. This survey was in the form of focus group discussions (FGDs) targeted at farmers and persons with experience in farming; and 14 key informant interviews (KIIs) targeting the principal agricultural experts at the province, district and/or village level. These surveys targeted farmers who have actively participated in farming in the respective villages for not less than 10 years. Quantitative data were collected using the stratified random sampling approach, where the provinces were used as the first level strata. Agroclimatic homogenous districts were selected from the selected provinces and then households were sampled randomly from these districts. The data were collected by use of a structured questionnaire and the final data comprised a sample size of 75 crop data from 25 households (i.e., one household might grow four crops). Data collection involved the use of focus group discussions (FGDs) administered to a total of 51 farmers (~55% women, 41% males, 4% youths) and 14 key informant interviews (KIIs). Local enumerators were trained on how to ask the various questions and also how to record the information. The villages were geo-referenced to enable easier identification in case of future follow-up programs.

Socioeconomic Characteristics of Households

The occupation categories of the respondents ranged from formal salaried worker to self employed in the farm. Farmers who are self-employed in the farm comprised over 89% of the sampled population. This is an indicator that most of the households have farming as their main occupation. The formal salaried male respondents comprised 9.7%, and the numbers were lower for female respondents. Land ownership and tenure determine level of investment a farmer is likely to have in the farm. Ownership varied in the sampled districts with about 15% of the land being titled. Of the farmers interviewed, Mabote district had the least number of farmers with titles while Machanga had most. However, a two-sample t-test

showed that land titling between farmers and between districts was not significantly different at 5% level of significance.

Table 15. A summary of expert ranking of crops' suitability in various districts

	Chibuto	Machanga	Mabote	Homoine
Maize	1	2	4	1
Millet		6	2	
Groundnut		7	7	5
Cassava		3		2
Sorghum		4	6	
Cashew nuts	6		1	6
Cow pea	3		3	4
Beans				
Rainfed rice		1		
Irrigated rice	2			
Vegetables	5	5	5	3
Sweet potato		8		
Water melon	4			

About 59% of farmers practice crop rotation as a form of income promotion and method to deal with crop failure (including from adverse weather). The practice was most common for farmers growing millet, which is commonly rotated with cow pea. Maize was found to be commonly rotated with most other crops. Mono-cropping was practiced by only a third of the farmers (N=51), while the rest practice intercropping. Table 16 shows crops that were grown by the respondents.

Table 16. Frequency of crops grown by respondents in Chibuto, Machanga, Homoine and Mabote districts

Crops	Chibuto	Machanga	Mabote	Homoine
Millet	0	0	4	0
Groundnut	2	5	3	4
Maize	4	5	2	5
Cassava	0	0	1	2
Cowpea	1	2	1	3
Beans	4	1	1	0
Rice		7		0

Crop 1. Maize: According to the field surveys, the crop requires deep, well-aerated, drained soils rich in organic matter that should be of good structure and fertile for high yields. Maize does well in soils with neutral ph level and if ph falls below 4.5, lime application is highly recommended. Calcium ammonium nitrate (CAN) fertilizers are recommended for topdressing though application rates are determined by soil requirement after soil has been

laboratory analyzed. Spacing is dependent on the agroecological zone and in high rainfall areas a spacing of 75 by 25 cm is recommended and that of 90 by 30 cm in low rainfall areas.

In terms of climatic hazards in Mozambique, maize is very susceptible to water logging that result in poor aeration and low temperatures affecting nutrient uptake. Concordantly, drought affects growth rate, retards silking and hastens pollen grain shading resulting to poor seed sets thus low yields or total crop failure. Low temperatures in some zones inhibit growth. Maize yield in Mozambique has been reported as averaging between 250-800kg/ha (Helder Lopes 2010).

Maize validation results: Manica has very high maize production, which is underestimated by the model if predicting production and not suitability. Manica area produces more maize than Sofala which the model shows to be very suitable. Areas in the north including Nampula, Cabo Delgado and Niassa are highly suitable, which is shown by the model. Like the north, the climate and soil condition are also suitable in the central, except in Tete Province. From Sofala northward, the model should indicate slightly higher suitability according to local farmers.

Crop 2. Millet: There are two main varieties of millet grown in Mozambique; Pearl millet and Finger millet. Pearl variety can tolerate alkalinity, salinity, and water logging conditions. Finger variety does well in low fertility soils. It relatively tolerates drought, withstands high temperature and does well in low fertile soils. In terms of agroclimatic conditions, millet grows in similar conditions like sorghum i.e. requires hot warm conditions of 28°C, altitude of 0 - 2000m above sea level and rainfall amount of 300 – 500mm per annum is enough for production. The crop production requirements is fine tilt, no fertilization is required and is mostly broadcasted or given a spacing of 45 by 45 cm when mono-cropped or 100 by 100 cm when intercropped. It requires weed control.

Millet validation results: The model prediction of millet suitability is true for the western side of the country which has semiarid conditions, required for millet production. However, production in the north is less than predicted. This area is much wetter for millet, and its condition for production is not as suitable as the model predicts according to the survey.

Crop 3. Rice: Rice is grown in a wide variety of environmental conditions because of its many types (tropical and temperate). Drought and flash flood in rainfed lowland areas due to irregular weather are major causes of crop losses in Mozambique. The production requirements differ depending on whether it's upland, rainfed or irrigated rice. Irrigated rice is found mostly in Chokwe and smaller irrigated schemes between Maputo and Chokwe. Other main rice growing zones (arranged from highest acreage to smallest) are Zambezia, Sofala, Nampula, Cabo Delgado, Gaza, Niassa, Inhambane, Manica and Tete. Most of the rice produced in Mozambique is rain fed and:

- Does well in clay/loamy soils that can retain high moisture
- For wet soils pre-germinated seeds are used while in dry soils seeds are used
- Seed rate of 50 – 80kg/ha and a planting depth of 3 -5 cm
- N management is essential and Ph application necessary in acid soils.

Rice validation results: The actual production of irrigated rice in the country is as predicted by the model according to agricultural experts. However, the model underestimates rice production in Chokwe district in the Gaza Province. Zambezia Province ranks second in rice production. The rice here is commercially produced by large scale private companies. Rainfed rice suitability is predicted well by the model. Agonia district in Nampula produces most of the rainfed rice, and has a husking factory located there. Rainfed rice also occurs in Beira region but on small scale. Farmers here use basic manual labour, and most of the rice produced is for domestic consumption and not for sale.

Crop 4. Beans: In terms of agroclimatic conditions beans do well at an altitude of 900 – 1200m above sea level and a temperature range of between 24 - 28°C. Water logging and drought are the main climatic hazards. However, where drought tolerant varieties are used, effects have been minimized. Extremely cold or hot temperatures inhibit growth and can lead to total crop failure. Beans are grown in all Provinces; however, most is concentrated in Nampula and Tete Provinces.

Bean validation results: The model output for the suitability of beans generally agrees with the actual distribution of the crop's productivity. According to agricultural experts, the predictions correspond to the areas where the yields of beans are highest in the country, determined by suitable soil, precipitation, and temperature. As the model shows, Lichinga in the north is the beans' production 'power house'. Agonia area is also suitable, and much of the beans consumed in Maputo originate from here. The model overestimates bean suitability in K(C)abora basa dam area, where the climate and soils are not suitable for bean production. Manica province is similar to Agonia in bean's soils and climate, and therefore is suitable for beans production. Chokwe and Xaixai are moderate bean producing areas which are very well predicted by the model.

Crop 5. Cassava: Cassava is grown in marginal areas (low altitude areas) and can grow in areas where temperatures are as high as 38°C. Since the crop is somewhat relatively drought resistant, low rainfall amounts are potentially suitable relative to other crops. Cassava requires well drained soils and does poorly in water logged soils. Cassava production is concentrated in four provinces; Cabo Delgado, Nampula, Zambezia and Inhambane. The four Provinces contribute about 93% of the national production (FAO/MIC, 2007).

Cassava validation results: The predicted suitability for cassava production in Nampula, Cabo Delgado and the coastal regions including Maxixe closely approximates the actual productivity. However, suitability in Lichinga may be overestimated because the district is very cold for cassava and the soils may be less suitable. If modeling productivity the model might show slightly higher productivity in Nyakuongo area of Inhambane Province areas.

Crop 6. Groundnuts: Most production in Mozambique is in the northern Provinces of Nampula (highest production and surplus), Zambezia and Cabo Delgado, which account for over 62% of production. Inhambane in the south accounts for about 17% of national

production. The crop needs at least 500mm of rainfall during the growing period. They are grown on slightly acidic, sandy to sandy-loamy soils and growing in heavier soils is not recommended. In the northern region the growing season is from early November to April. In the drier southern regions of the country, the growing season is from early September to late February. The national average is around 400kg/ha. A low average of 300kg/ha is recorded in the drier south while in the north yields range is 450-600 kg/ha.

Groundnut validation results: Predictions considered by agricultural experts to be in agreement with the actual groundnut productivity in the country.

Crop 7. Potato: Potatoes do well in highlands at the altitude of 1500 – 3000m above sea level, rainfalls above 600mm and daily temperature of 15 -18°C. Potato grows in a wide range of soils but is suited to acidic soils with a pH of 4.5 to 5.5. Light soils are the best for potato production and NPK 12:24:12 fertilizers are recommended. Potato is produced in 9 Provinces of Mozambique. The districts of Angonia and Tsangano in Tete Province account for about 90% of the national production. Niassa Province is second most producing province followed by Zambezia, Manica, Maputo, Nampula, Inhambane, Gaza and Sofala. In Maputo and Manica Provinces, production is through irrigation between March and August with a second irrigated crop from July to October. In Tsangano, Angonia and Lichinga Districts, 2 -3 crops are possible. Rain fed crop is from November to March and 1 or 2 irrigated crops between March and October. In Manica the planting period is March to August.

Potato validation results: Potato suitability predicted by the model corresponds to the actual production. The government has begun promoting potato production in Chokwe and Maamba district of Maputo province near the South African border. The agroclimatic conditions in the predicted areas is suitable for potato production, according to agricultural experts.

Crop 8. Tobacco: Tobacco can be grown in marginal areas (low altitude areas) and optimum temperature range of 24- 30°C and a rainfall above 900mm. It prefers slightly acidic soils with ph level of 6-6.5 and fertile clay loamy soil. The crop needs high fertilizer inputs before it fully matures and being commercial, markets have to be available before production is started. Climatic changes have caused heavy losses to tobacco farmers. Flooding and drought are the major hazards affecting most farms and though drought tolerant varieties are being used, there uptake has been slow. Weather forecasting has not helped much and thus the farmers are not adequately prepared for floods or drought.

Tobacco validation results: The model prediction for tobacco suitability is correct for most regions, except in Nampula region where production is underestimated if estimating production. Nampula region hosts two tobacco processing companies, a reflection of its suitability.

Sample interview comments:

Comments of the District Director of economic affairs in Chibuto:

“Climate change has affected the region. The crop season used to be 2 seasons but now are 3 seasons. People plant irrespective of season as a consequence, it’s not clear the seasons anymore. If we follow the regular calendar, this time there would be no crops but now there are [October]... This contributes to more crop diseases due to continuous cropping. Last season there was a mice/rodent epidemic followed by coldest weather, therefore beans did not produce well. For cash crops like cashew nuts – rains come out of the season disrupts the normal cycle. Distribution of rain has not been the same. It has been lower and higher in other regions. The most difficult has been to change the mentality- to change to tolerant crops. Introduce people to cope with the situation (e.g., sorghum) not grown because of birds and pests.”



Pictures 1 & 2: Local famer interviews and model assesment.



Picture 3: Interview session with farmers who are producers in Chibuto district.



Picture 4: Chibuto FGD, A session of focused group discussion in Chibuto



Picture 5: Drier elevated foreground and wetter background on a lower elevation.

Objective 4 Conclusions

- Language barriers, travel, facilities planning, and timelines created challenges in collecting and analyzing data
- Key factors cited as influencing crop choice include agroclimatic conditions, markets, labour, pests, and diseases. For instance, in the past, farmers in Machanga mainly grew millet and sorghum as these crops are more drought tolerant. However, labour needed to protect the crop from pests has steadily declined, as more and more children go to school, affecting the production of these crops. Today most farmers have diversified their production in response to weather variability, labour constraints, and market needs.
- Rankings of crop suitability by experts varied across regions; for example, experts ranked cashew nuts of low suitability in Chibuto and Homoine with high suitability in Mabote while maize ranked high in Chibuto and Homoine with a modest ranking in Mabote
- About 59% of farmers practice crop rotation as a strategy to adapt to variability and lower risks; maize was found to be a commonly rotated crop
- In general the model results performed well with some local specificity errors; for example, maize areas in the north including Nampula, Cabo Delgado and Niassa are highly suitable, which is well shown by the model however production is underestimated in Manica.
- Suitability of beans was found to be accurate; the predictions correspond to the areas where the yields of beans are highest in the country, determined by suitable soil, precipitation and temperature. As the model shows, Lichinga in the north is the beans' production 'power house'. The model overestimates bean suitability in Cahora basa dam area, where the climate and soils are not suitable for bean production. Chokwe and Xaixai are moderate bean producing areas which are very well predicted by the model.
- The predicted suitability for cassava production in Nampula, Cabo Delgado and the coastal regions including Maxixe closely approximates the actual productivity. However, suitability in Lichinga may be overestimated because the district is too cool for cassava, and the soils may be less suitable according to farmers. Sofala does not produce as much cassava as the model predicts. The area has perceived poor soil conditions and the climate is not suitable for cassava production according to locals
- The model prediction for tobacco suitability is correct for most regions, except in Nampula region where production is underestimated
- Access to key inputs is also low; underdeveloped capital markets and harvest losses also contribute to decreased productivity

Recommendations

- Higher resolution inputs variables (including crop maps, crop growth and yield parameters, and fertilizer use) will potentially improve the precision of modeling outputs, vulnerability assessment, and risk products
- Linking with short-term numerical weather simulations can provide real time risk maps at temporal intervals useful for enacting adaptation strategies and disaster management
- Spatial boot-strapping and / or Monte Carlo uncertainty assessments can enhance predictive capabilities, scenario risks, and uncertainty analysis
- Rainfall intensity shifts and rainfall timing should be investigated in the context of yield and vulnerability
- Appropriate and ample time for field campaign spin up and in-field activities should be incorporated into future efforts as field work, travel, and logistical organizing can be time consuming in Mozambique
- Web-GIS visualization and delivery mechanisms can likely enhance the use of the products and distribution

Acknowledgements

We thank and acknowledge contributions from Edgar Misael Uribe for weather station data and the World Bank Agricultural Risk Management Team for project oversight.

References

Akaike, H. 1974. New look at statistical-model identification. IEEE Transactions on Automatic Control AC19: 716-23.

AFTS. Mozambique agricultural development strategy. Stimulating smallholder agriculture growth. Report # 32416-MZ.

Coughlin, P. 2006. Agricultural intensification in Mozambique. Infrastructure, policy, and institutional framework. Final report.

DNDC, 2010. DeNitrification-DeComposition Model, version 9.4.

FAO, 2010. FAO Crop Calendar. URL: <http://www.fao.org/agriculture/seed/cropcalendar/welcome.do>. Accessed August, 2011

FAO, 2010. FAOSTAT. URL: <http://faostat.fao.org/>. Accessed August 2011

FAO/IIASA/ISRIC/ISSCAS/JRC, 2009. *Harmonized World Soil Database (version 1.1)*. FAO, Rome, Italy and IIASA, Laxenburg, Austria.

Funk, C., Dettinger, M., Michaelsen, J., Verdin, J., Brown, M., Barlow, M., Hoell, A. 2008. Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development. PNAS. 105, n. 32, 11081-11086.

- Helder Lopes. 2010. Adoption of improved maize and common bean varieties in Mozambique. Master's thesis. Department of agricultural economics, Michigan State University.
- Hutchinson, M.F. 1998. Interpolation of rainfall data with thin-plate smoothing splines ii: Analysis of topographic dependence. *Journal of Geographic Information and Decision Analysis* 2: 168-85.
- INGC. 2009. Main report: INGC Climate Change Report: Study on the Impact of Climate Change on Disaster Risk in Mozambique. [Asante, K., Brundrit, G., Epstein, P., Fernandes, A., Marques, M.R., Mavume, A, Metzger, M., Patt, A., Queface, A., Sanchez del Valle, R., Tadross, M., Brito, R. (eds.)]. INGC, Mozambique.
- Jarvis, A., H.I. Reuter, A. Nelson, E. Guevara, 2008, Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRTM 90m Database.
- Li C, Frohling S, Frohling TA, 1992. A model of nitrous oxide evolution from soil driven by rainfall events: 2. model applications. *Journal of Geophysical Research* 97: 9777-9783.
- Li C, Qiu J, Frohling S, Xiao X, Salas W, Moore B, Boles S, Huang Y, Sass R, 2002. Reduced methane emissions from large-scale changes in water management of China's rice paddies during 1980-2000. *Geophysical Research Letters* 29: 1972. doi:10.1019/2002GL015370.
- Li, C., N. Farahbakhshazad, D.B. Jaynes, D.L. Dinnes, W. Salas, D. McLaughlin, 2006. Modeling nitrate leaching with a biogeochemical model modified based on observations in a row-crop field in Iowa. *Ecological Modeling* 196:116-130.
- Loening and Perumalpillai-Essex 2005. Agriculture and rural poverty in Mozambique: Dimensions, profiles, and trends. Background paper for the 2005 Rural Development Strategy. Washington, DC. World Bank.
- Monfreda et al. 2008. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, Vol.22, GB1022, doi:10.1029/2007GB002947
- Moore N , G Alagarswamy, B Pijanowski, P Thornton, B Lofgren, J Olson, J Andresen, P Yanda, J Qi, 2011. East African Food Security as Influenced by Future Climate Change and Land Use Change at Local to Regional Scales, *Climatic Change*, DOI: 10.1007/s10584-011-0116-7.
- NASA, 2010. Modern Era Retrospective-Analysis For Research and Applications (MERRA). URL: <http://gmao.gsfc.nasa.gov/merra/>. Accessed August 2011
- PEDSA 2010. Strategic plan for agricultural development. Republic of Mozambique: Ministry of Agriculture. October 2010.
- Ramankutty et al. 2008. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles*, Vol. 22, GB1003, doi:10.1029/2007GB002952
- Rienecker, M. et al 2009. MERRA- NASA's Reanalysis overview of the system. AMS, January, 2009.

Sacks, W.J., D. Deryng, J.A. Foley, and N. Ramankutty (2010). Crop planting dates: An analysis of global patterns. *Global Ecology and Biogeography*, 19: 607-620.

Wan Z, Zhang Y, Zhang Q, Li ZL. 2002. Validation of the land-surface temperature product retrieved from Terra Moderate Resolution Imaging Spectroradiometer data. *Remote Sensing of Environment* **83**(1-2): 163-180.

Wan Z, Wang P, Li X, Wan Z. 2004. Using MODIS land surface temperature and normalized difference vegetation index for monitoring drought in the southern Great Plains, USA. *International Journal of Remote Sensing* **25**: 61-72.

Wan Z. 2008. New refinements and validation of the MODIS land-surface temperature/emissivity products. *Remote Sensing of Environment* **112**: 59-74.

Wolff, D. B, D. A. Marks, E. Amitai, D. S. Silberstein, B. L. Fisher, A. Tokay, J. Wang, and J. L. Pippitt, 2004: Ground Validation for Tropical Rainfall Measuring Mission (TRMM). *J. Atmos. Ocean. Tech*

Appendix 1. Monthly TRMM ppt totals by Province (n=10)

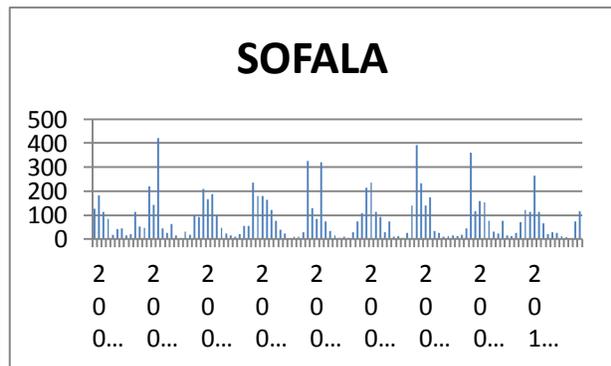
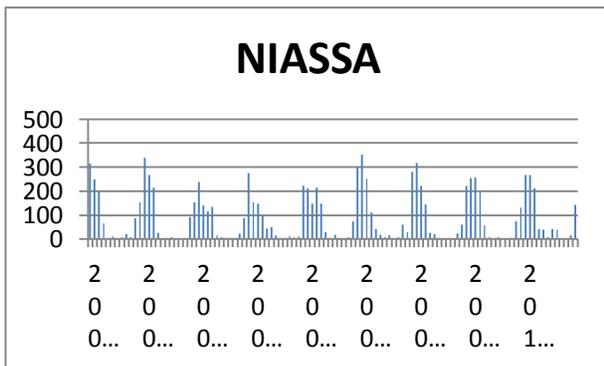
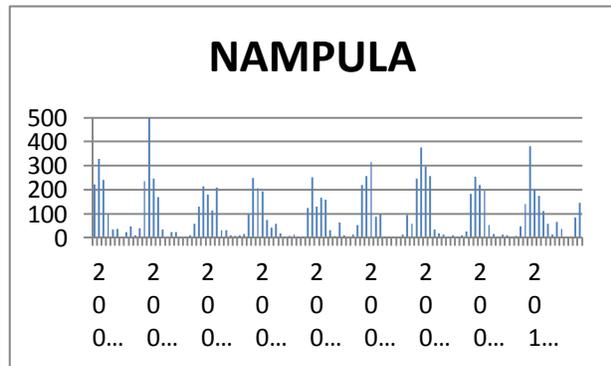
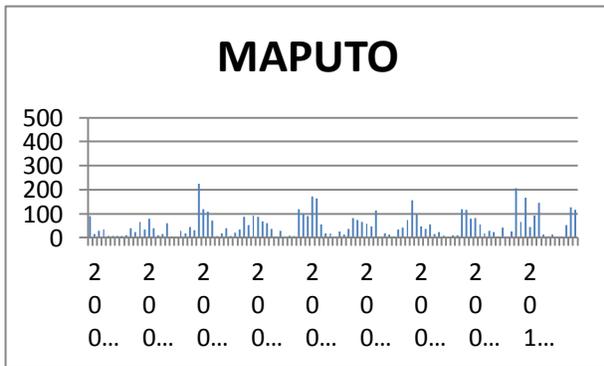
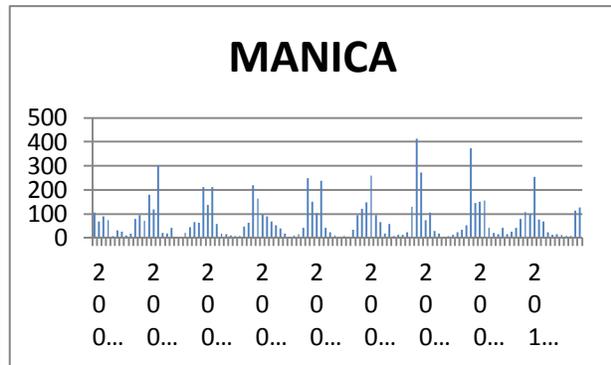
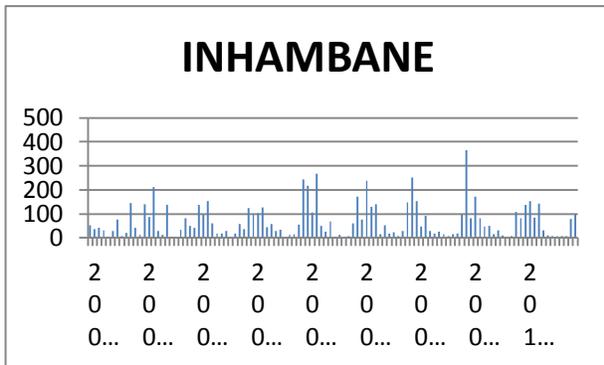
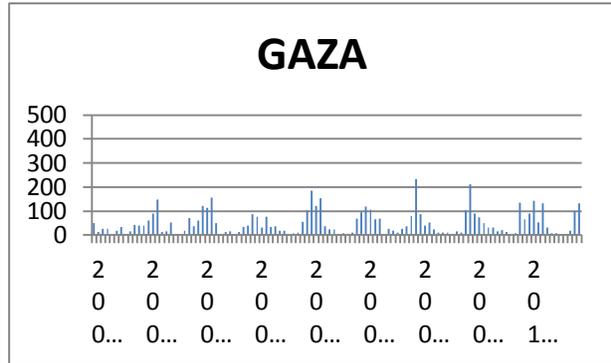
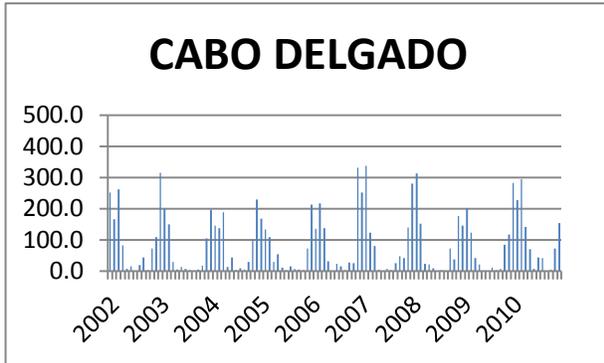
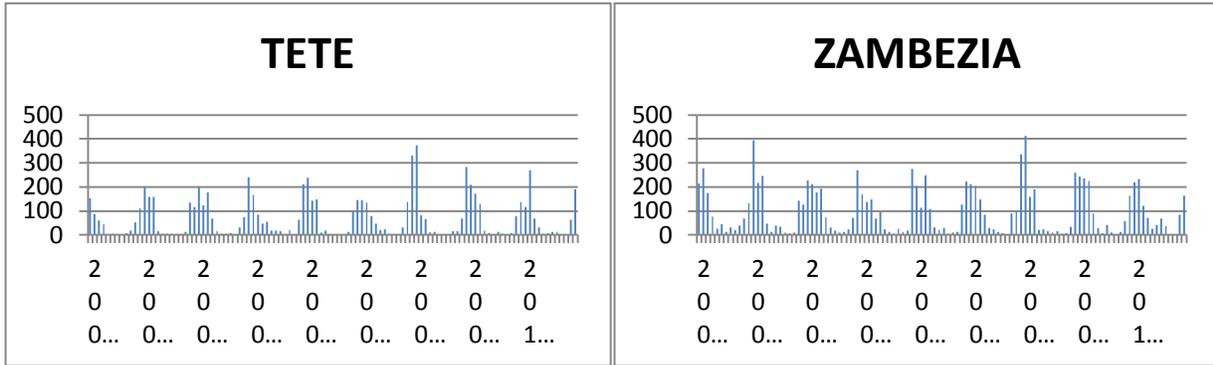
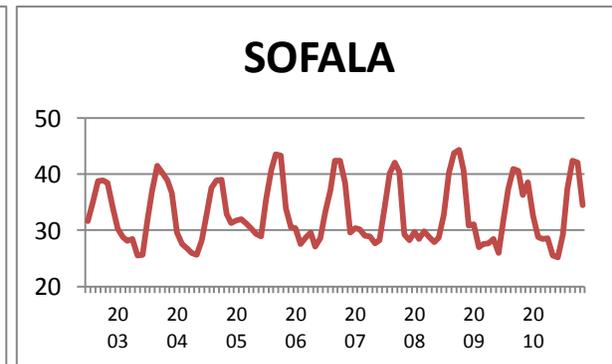
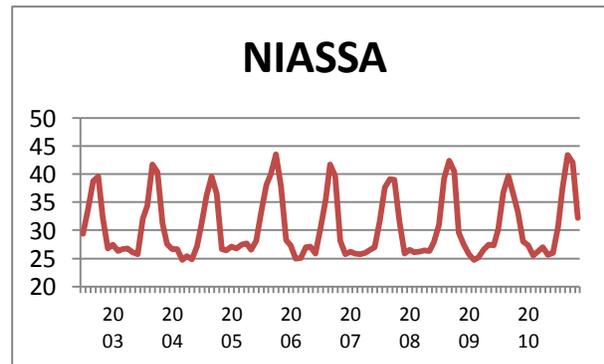
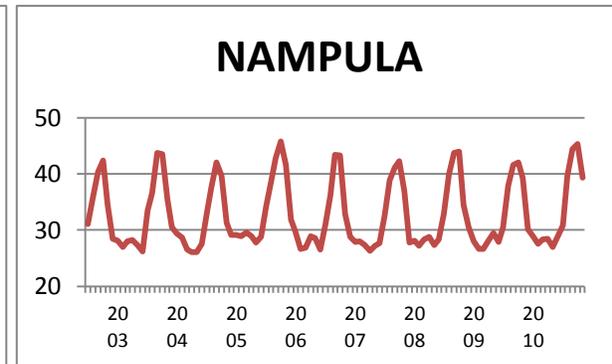
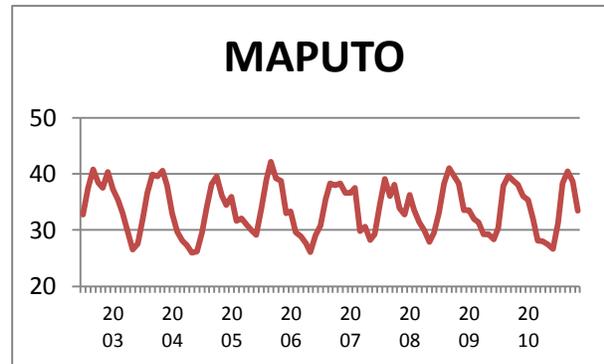
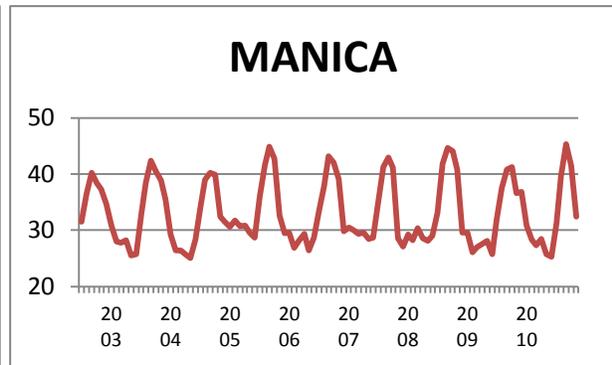
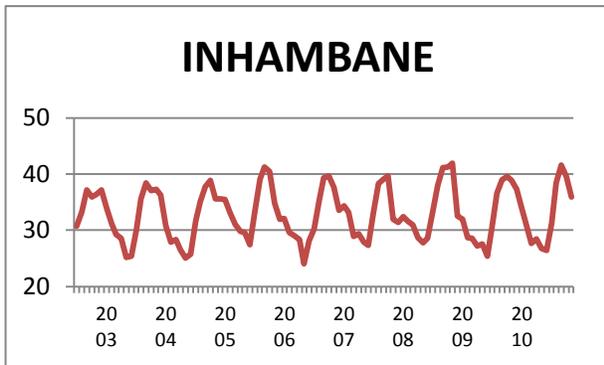
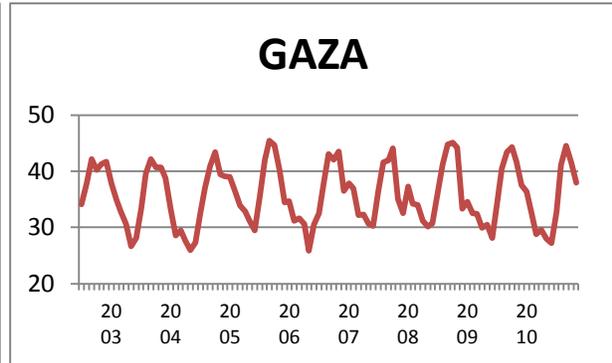
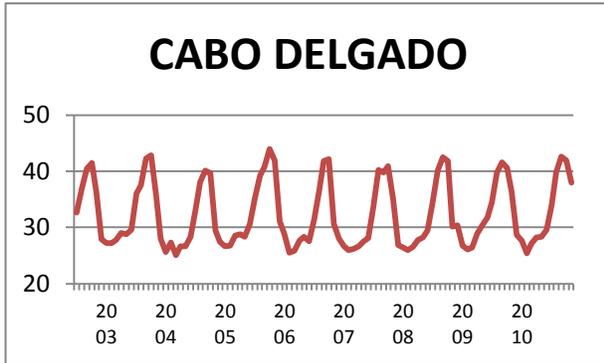
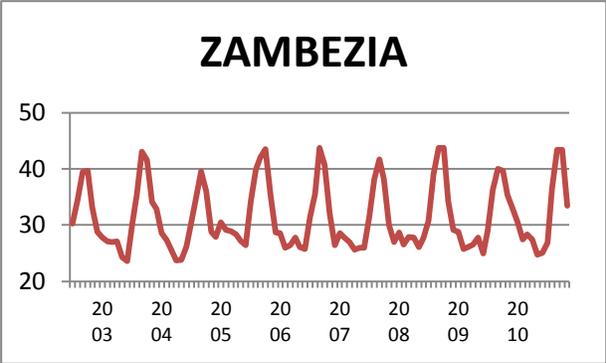
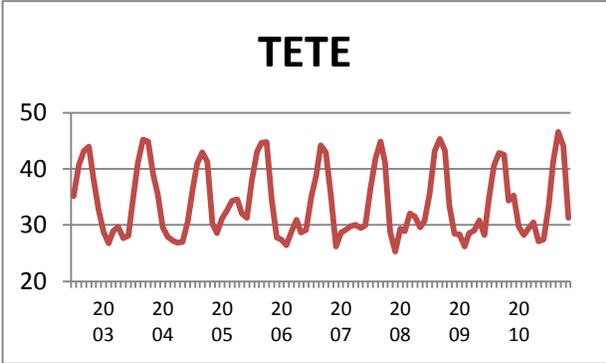


Figure continued ...

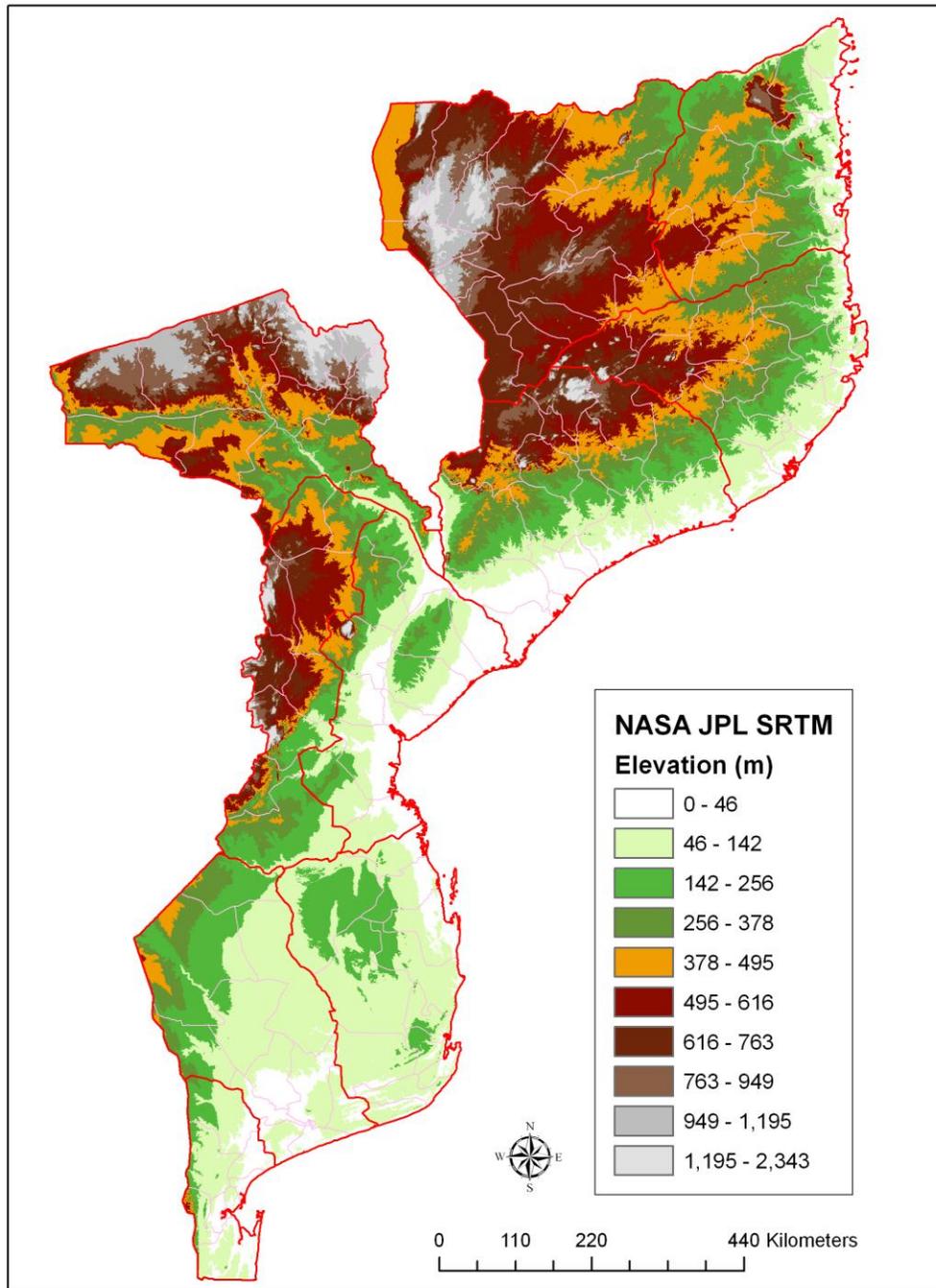


Appendix 2. Monthly MODIS LST by Province (n=10)

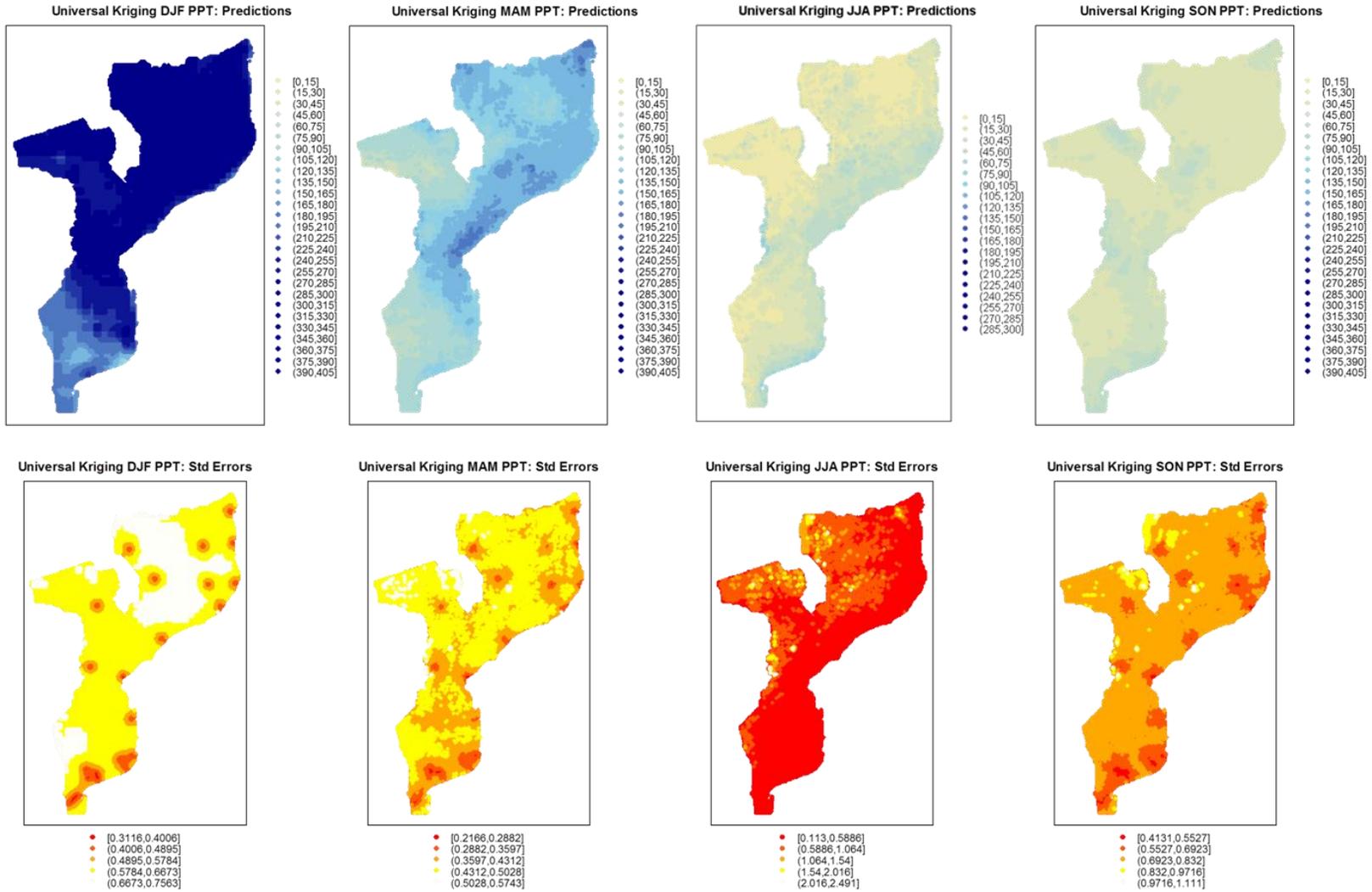




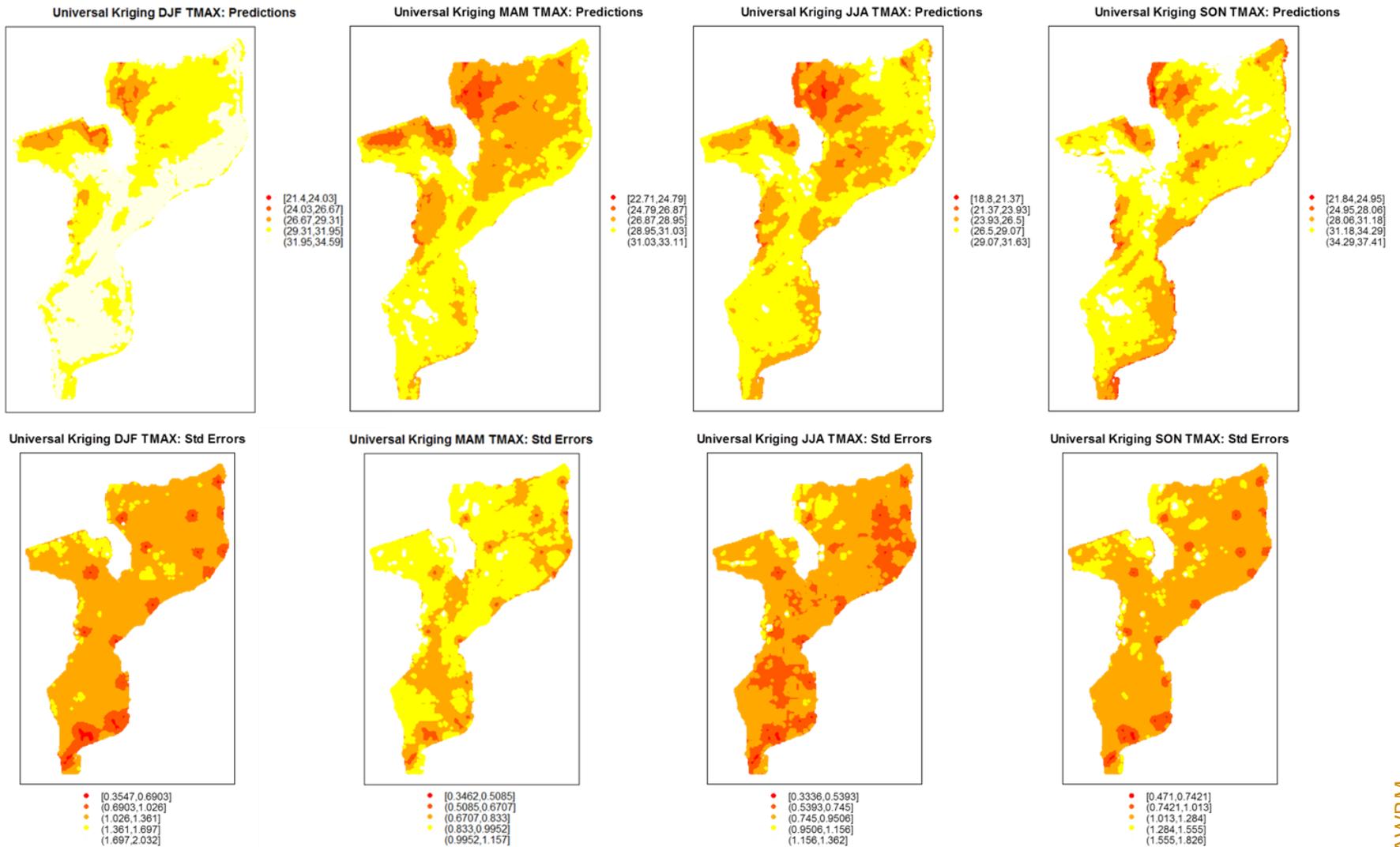
Appendix 3. SRTM DEM



Appendix 4. UK seasonal predictions and S.E.



Appendix 5. LST UK T-max & T-mean¹ seasonal predictions and S.E.



Appendix 6. 10 year average climate - PCA

10 year average climate - PCA identified 5 components

Latent Roots (Eigenvalues)

	1	2	3	4	5
	3.841	1.875	1.005	0.995	0.724

Component loadings	6	7	8	9
	0.329	0.181	0.050	0.001

	1	2	3	4	5
X	0.324	0.868	-0.003	0.002	0.211
P	0.000	0.019	0.720	0.693	-0.031
Q	0.019	0.011	0.697	-0.717	-0.021
LAVG10	-0.603	-0.286	0.044	0.004	0.708
Y	0.765	0.373	0.012	0.005	0.392
PAVG10	0.632	0.609	-0.010	-0.002	-0.109
MEANLONGCONV	-0.877	0.413	-0.006	-0.005	-0.096
MEANELEV5KM	0.900	-0.423	0.003	0.005	0.026
MEANMAXCRV5K	0.899	-0.425	0.003	0.005	0.023

Variance Explained by Components

	1	2	3	4	5
	3.841	1.875	1.005	0.995	0.724
Percent of Total Variance Explained	1	2	3	4	5
	42.675	20.831	11.171	11.052	8.047

Rotated Loading Matrix (VARIMAX, Gamma = 1.0000)

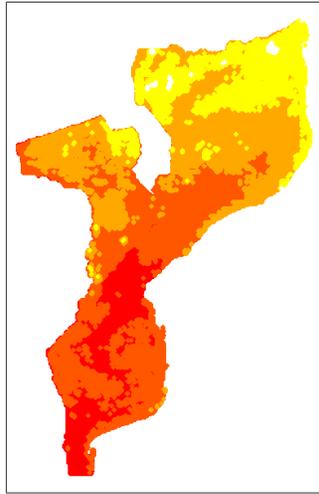
	1	2	3	4	5
MEANELEV5KM	0.979	0.073	-0.001	0.004	0.160
MEANMAXCRV5K	0.979	0.070	-0.001	0.004	0.162
MEANLONGCONV	-0.965	-0.097	0.001	-0.004	-0.091
X	-0.161	0.928	0.004	0.002	0.128
Y	0.497	0.795	0.004	0.006	-0.019
PAVG10	0.186	0.735	0.004	0.009	0.455
P	-0.002	0.006	1.000	0.003	-0.003
Q	0.007	0.008	0.003	1.000	0.000
LAVG10	-0.246	-0.233	0.005	0.001	-0.914

COMPONENTS: Elevation Ppt and loc P: Northness Q: Eastness LST

"Variance" Explained by Rotated Components

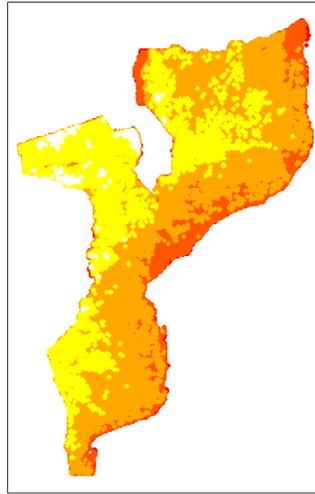
	1	2	3	4	5
	3.215	2.106	1.000	1.000	1.119
Percent of Total Variance Explained	1	2	3	4	5
	35.720	23.402	11.111	11.112	12.431

Factor 1 Scores - 10 YR AVG Climate



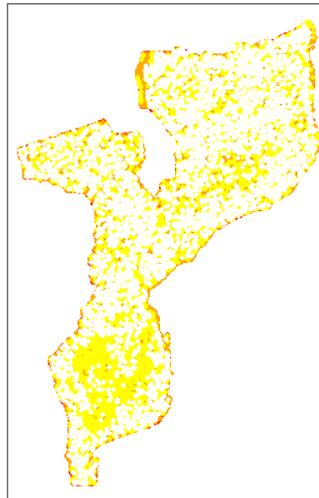
- [-2.148,-1.025]
- [-1.025,0.09735]
- [0.09735,1.22]
- [1.22,2.342]
- [2.342,3.465]

Factor 2 Scores - 10 YR AVG Climate



- [-3.593,-2.104]
- [-2.104,-0.6159]
- [-0.6159,0.8725]
- [0.8725,2.361]
- [2.361,3.849]

Factor 3 Scores - 10 YR AVG Climate



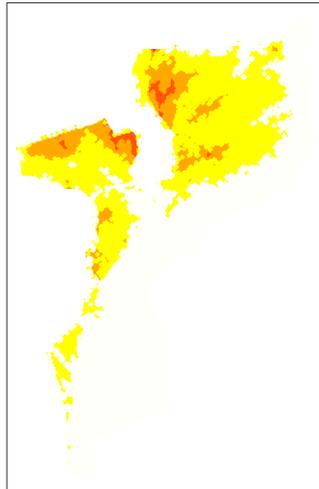
- [-1.889,-1.13]
- [-1.13,-0.3715]
- [-0.3715,0.3871]
- [0.3871,1.146]
- [1.146,1.904]

Factor 4 Scores - 10 YR AVG Climate



- [-6.899,-5.285]
- [-5.285,-3.67]
- [-3.67,-2.056]
- [-2.056,-0.441]
- [-0.441,1.174]

Factor 5 Scores - 10 YR AVG Climate



- [-4.741,-3.455]
- [-3.455,-2.169]
- [-2.169,-0.8829]
- [-0.8829,0.4033]
- [0.4033,1.689]

Appendix 7. 10 year average DJF climate - PCA

Latent Roots (Eigenvalues)

	1	2	3	4	5
	4.478	1.730	1.005	0.995	0.292
	6	7	8	9	
	0.253	0.192	0.054	0.001	

Component loadings

	1	2	3	4	5
X	0.336	0.878	-0.014	0.001	0.193
P	0.001	0.024	0.713	-0.701	-0.005
Q	0.019	0.013	0.704	0.710	-0.004
LAVG10DJF	-0.853	-0.208	0.016	0.001	0.465
MEANLONGCONV	-0.870	0.422	-0.005	0.005	-0.157
PAVG10DJF	0.803	0.408	-0.005	0.002	0.077
MEANELEV5KM	0.889	-0.438	0.004	-0.005	0.063
MEANMAXCRV5K	0.888	-0.440	0.005	-0.005	0.057
Y	0.810	0.430	-0.005	-0.002	0.034

Variance Explained by Components

	1	2	3	4	5
	4.478	1.730	1.005	0.995	0.292

Percent of Total Variance Explained

	1	2	3	4	5
	49.760	19.221	11.165	11.052	3.245

Rotated Loading Matrix (VARIMAX, Gamma = 1.0000)

	1	2	3	4	5
MEANELEV5KM	0.972	0.113	-0.002	0.004	0.167
MEANMAXCRV5K	0.972	0.110	-0.002	0.004	0.172
MEANLONGCONV	-0.967	-0.141	0.001	-0.004	-0.074
X	-0.187	0.941	0.004	0.002	0.003
Y	0.414	0.778	0.006	0.007	0.254
PAVG10DJF	0.430	0.767	0.002	0.010	0.209
P	-0.002	0.006	1.000	0.003	-0.001
Q	0.006	0.008	0.003	1.000	0.001
LAVG10DJF	-0.475	-0.495	0.004	-0.001	-0.719

COMPONENTS: Elevation Ppt and loc P: Northness Q: Eastness LST

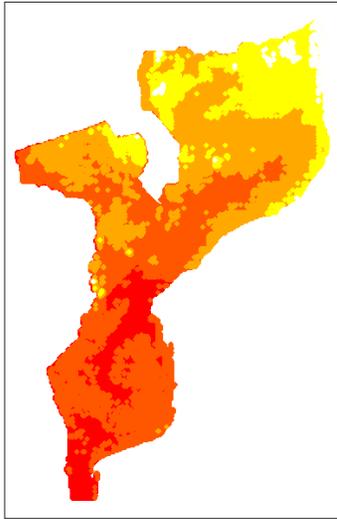
"Variance" Explained by Rotated Components

	1	2	3	4	5
	3.441	2.370	1.000	1.000	0.688

Percent of Total Variance Explained

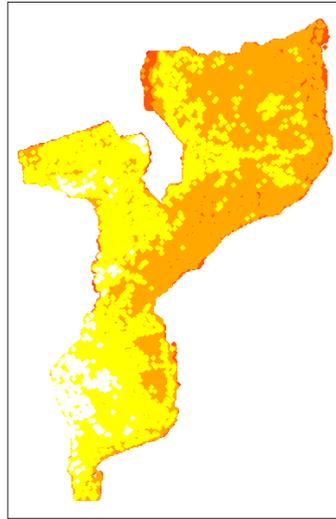
	1	2	3	4	5
	38.238	26.336	11.111	11.112	7.645

Factor 1 Scores - DJF 10 YR AVG Climate



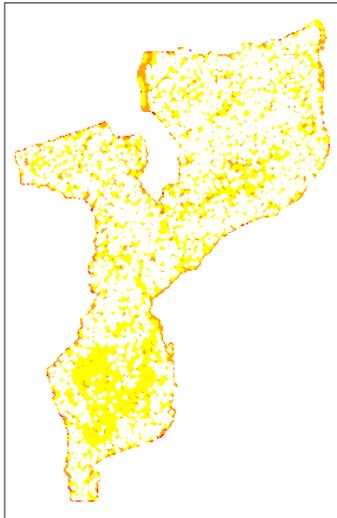
- [-2.148,-1.046]
- [-1.046,0.05681]
- [0.05681,1.159]
- [1.159,2.262]
- [2.262,3.365]

Factor 2 Scores - DJF 10 YR AVG Climate



- [-4.089,-2.522]
- [-2.522,-0.9543]
- [-0.9543,0.6133]
- [0.6133,2.181]
- [2.181,3.748]

Factor 3 Scores - DJF 10 YR AVG Climate



- [-1.899,-1.138]
- [-1.138,-0.3769]
- [-0.3769,0.3841]
- [0.3841,1.145]
- [1.145,1.906]

Factor 4 Scores - DJF 10 YR AVG Climate



- [-6.933,-5.311]
- [-5.311,-3.689]
- [-3.689,-2.067]
- [-2.067,-0.4446]
- [-0.4446,1.178]

Factor 5 Scores - DJF 10 YR AVG Climate



- [6.101,4.34]
- [4.34,2.578]
- [2.578,-0.8173]
- [-0.8173,0.9439]
- [0.9439,2.705]

Conclusion: Use 125 (elev, loc&ppt, temp)

Appendix 8. 10 year average MAM climate - PCA

10 year average MAM climate

Latent Roots (Eigenvalues)

	1	2	3	4	5
	3.799	2.210	1.005	0.995	0.547
	6	7	8	9	
	0.211	0.180	0.053	0.001	

Component loadings

	1	2	3	4	5
X	0.313	0.853	-0.000	0.001	-0.295
PAVG10MAM	0.257	0.848	-0.011	-0.004	0.351
P	0.000	0.015	0.713	0.701	0.013
Q	0.018	0.008	0.704	-0.710	0.010
Y	0.769	0.366	0.009	0.003	-0.448
LAVG10MAM	-0.777	-0.395	0.023	-0.003	-0.367
MEANMAXCRV5K	0.908	-0.401	0.000	0.003	0.033
MEANELEV5KM	0.909	-0.399	0.000	0.003	0.031
MEANLONGCONV	-0.888	0.390	-0.002	-0.004	-0.003

Variance Explained by Components

	1	2	3	4	5
	3.799	2.210	1.005	0.995	0.547
Percent of Total Variance Explained	1	2	3	4	5
	42.206	24.558	11.170	11.052	6.078

Rotated Loading Matrix (VARIMAX, Gamma = 1.0000)

	1	2	3	4	5
MEANMAXCRV5K	-0.991	0.029	-0.002	0.004	0.059
MEANELEV5KM	-0.991	0.029	-0.002	0.004	0.062
MEANLONGCONV	0.966	-0.010	0.001	-0.004	-0.081
LAVG10MAM	0.530	-0.753	0.005	0.005	-0.216
PAVG10MAM	0.140	0.892	0.004	0.007	0.307
P	0.002	0.001	1.000	0.003	0.005
Q	-0.007	0.003	0.003	1.000	0.006
X	0.131	0.486	0.005	0.003	0.812
Y	-0.487	0.193	0.005	0.007	0.807

COMPONENTS: Elevation Ppt and LST P: Northness Q: Eastness Location

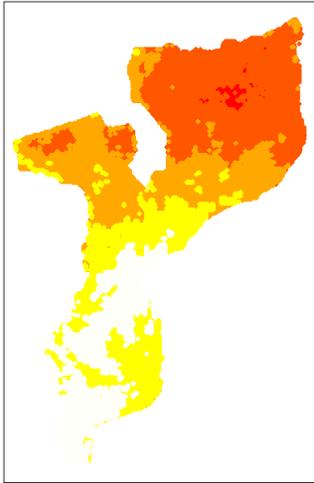
"Variance" Explained by Rotated Components

	1	2	3	4	5
	3.453	1.638	1.000	1.000	1.464

Percent of Total Variance Explained

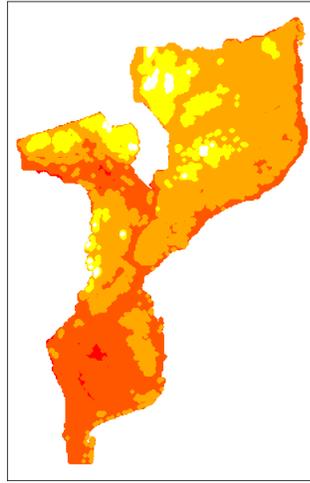
	1	2	3	4	5
	38.369	18.202	11.112	11.112	16.270

Factor 1 Scores - MAM 10 YR AVG Climate



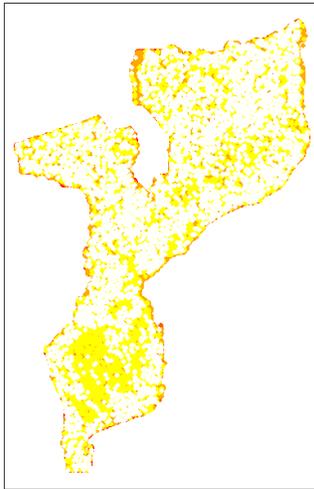
- [-2.378,-1.475]
- [-1.475,-0.5719]
- [-0.5719,0.3314]
- [0.3314,1.235]
- [1.235,2.138]

Factor 2 Scores - MAM 10 YR AVG Climate



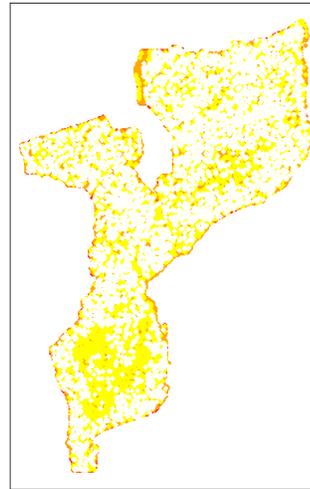
- [-3.405,-1.854]
- [-1.854,-0.3035]
- [-0.3035,1.247]
- [1.247,2.798]
- [2.798,4.349]

Factor 3 Scores - MAM 10 YR AVG Climate



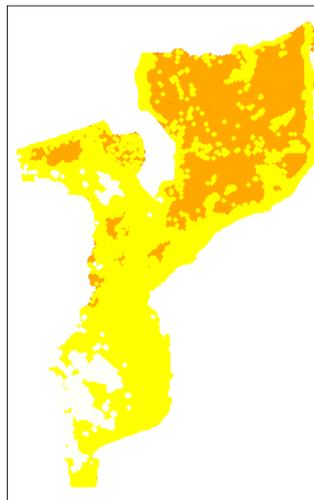
- [-1.901,-1.141]
- [-1.141,-0.3804]
- [-0.3804,0.3796]
- [0.3796,1.14]
- [1.14,1.9]

Factor 4 Scores - MAM 10 YR AVG Climate



- [-1.89,-1.13]
- [-1.13,-0.3698]
- [-0.3698,0.3903]
- [0.3903,1.151]
- [1.151,1.911]

Factor 5 Scores - MAM 10 YR AVG Climate



- [-5.673,-3.837]
- [-3.837,-2.002]
- [-2.002,-0.1669]
- [-0.1669,1.668]
- [1.668,3.504]

Conclusion: Use 125 (elev, ppt & temp, loc)

Appendix 9. 10 year average JJA climate - PCA

Latent Roots (Eigenvalues)

	1	2	3	4	5
	3.720	1.492	1.270	1.004	0.995
	6	7	8	9	
	0.326	0.142	0.051	0.001	

Component loadings

	1	2	3	4	5
MEANELEV5KM	0.968	-0.085	-0.191	0.011	-0.006
MEANMAXCRV5K	0.968	-0.088	-0.192	0.011	-0.006
X	0.072	0.931	0.278	-0.033	0.003
LAVG10JJA	-0.124	-0.430	0.835	-0.032	0.006
Q	0.018	0.019	0.041	0.711	0.701
P	-0.002	0.021	0.056	0.703	-0.709
MEANLONGCONV	-0.947	0.084	0.155	-0.009	0.006
PAVG10JJA	-0.680	0.355	-0.474	0.028	-0.003
Y	0.681	0.539	0.410	-0.034	0.002

Variance Explained by Components

	1	2	3	4	5
	3.720	1.492	1.270	1.004	0.995

Percent of Total Variance Explained

	1	2	3	4	5
	41.336	16.580	14.106	11.155	11.051

Rotated Loading Matrix (VARIMAX, Gamma = 1.0000)

	1	2	3	4	5
MEANMAXCRV5K	-0.988	0.051	-0.054	0.004	-0.001
MEANELEV5KM	-0.988	0.054	-0.054	0.004	-0.001
MEANLONGCONV	0.961	-0.066	0.024	-0.004	0.000
PAVG10JJA	0.638	-0.032	-0.636	-0.000	0.005
Y	-0.508	0.795	0.184	0.006	0.004
X	0.124	0.954	-0.157	0.004	0.005
LAVG10JJA	0.192	-0.058	0.927	0.004	0.007
Q	-0.007	0.007	0.003	1.000	0.003
P	0.002	0.006	0.004	0.003	1.000

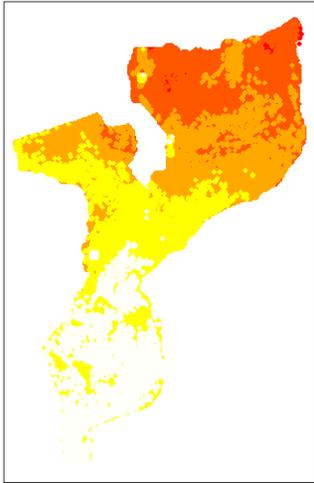
COMPONENTS: Elevation & ppt Location LST Q: Eastness P: Northness
 "Variance" Explained by Rotated Components

	1	2	3	4	5
	3.595	1.556	1.329	1.000	1.000

Percent of Total Variance Explained

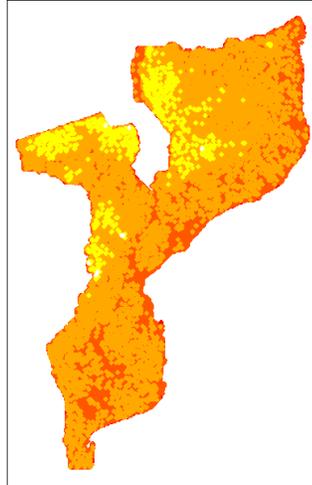
	1	2	3	4	5
	39.945	17.294	14.766	11.111	11.112

Factor 1 Scores - JJA 10 YR AVG Climate



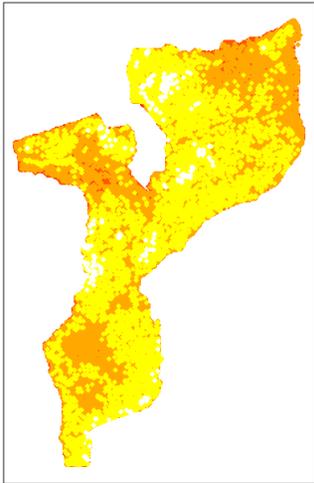
- [-2.571,-1.605]
- [-1.605,-0.6403]
- [-0.6403,0.3248]
- [0.3248,1.29]
- [1.29,2.255]

Factor 2 Scores - JJA 10 YR AVG Climate



- [-2.561,-1.064]
- [-1.064,0.4335]
- [0.4335,1.931]
- [1.931,3.428]
- [3.428,4.925]

Factor 3 Scores - JJA 10 YR AVG Climate



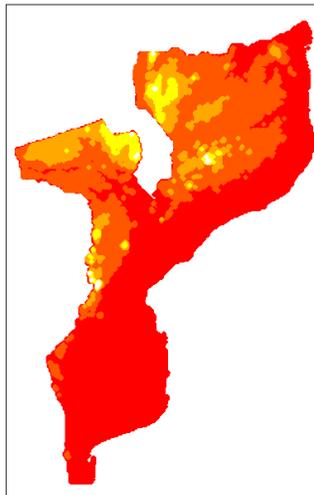
- [-3.366,-1.975]
- [-1.975,-0.5834]
- [-0.5834,0.8078]
- [0.8078,2.199]
- [2.199,3.59]

Factor 4 Scores - JJA 10 YR AVG Climate



- [-6.921,-5.305]
- [-5.305,-3.688]
- [-3.688,-2.072]
- [-2.072,-0.455]
- [-0.455,1.162]

Factor 5 Scores - JJA 10 YR AVG Climate



- [-1.216,0.07355]
- [0.07355,1.363]
- [1.363,2.652]
- [2.652,3.941]
- [3.941,5.23]

Conclusion: Use elev & ppt, loc, temp, q, p (145)

Appendix 10. 10 year average SON climate - PCA

10 year average SON climate

Latent Roots (Eigenvalues)

	1	2	3	4	5
	3.349	1.895	1.045	1.005	0.994
	6	7	8	9	
	0.496	0.166	0.049	0.001	

Component loadings

	1	2	3	4	5
MEANELEV5KM	0.954	-0.281	0.030	0.001	0.006
MEANMAXCRV5K	0.953	-0.284	0.032	0.002	0.007
MEANLONGCONV	-0.936	0.271	0.053	0.005	-0.001
X	0.187	0.850	0.193	0.007	0.017
PAVG10SON	-0.262	-0.779	0.173	0.033	0.019
LAVG10SON	-0.028	0.003	-0.979	-0.078	-0.072
Q	0.020	0.016	-0.006	0.719	-0.694
P	0.000	0.021	-0.115	0.693	0.711
Y	0.742	0.578	-0.037	-0.011	0.001

Variance Explained by Components

	1	2	3	4	5
	3.349	1.895	1.045	1.005	0.994

Percent of Total Variance Explained

	1	2	3	4	5
	37.211	21.061	11.607	11.161	11.049

Rotated Loading Matrix (VARIMAX, Gamma = 1.0000)

	1	2	3	4	5
MEANMAXCRV5K	0.993	0.036	0.039	0.004	-0.002
MEANELEV5KM	0.993	0.039	0.036	0.004	-0.002
MEANLONGCONV	-0.974	-0.045	0.047	-0.004	0.001
Y	0.517	0.785	-0.027	0.007	0.006
X	-0.096	0.863	0.201	0.004	0.009
PAVG10SON	0.001	-0.823	0.168	-0.002	0.005
LAVG10SON	-0.021	0.003	-0.985	-0.000	0.004
Q	0.007	0.007	0.000	1.000	0.003
P	-0.002	0.005	-0.004	0.003	1.000

COMPONENTS: Elevation Loc & ppt LST Q: Eastness P: Northness

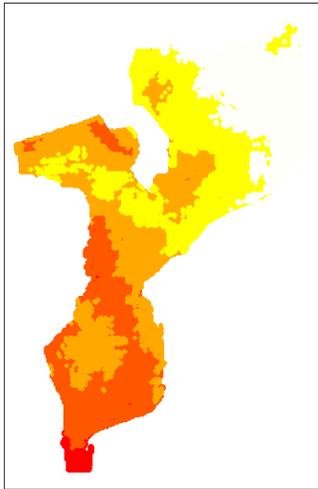
"Variance" Explained by Rotated Components

	1	2	3	4	5
	3.199	2.044	1.044	1.000	1.000

Percent of Total Variance Explained

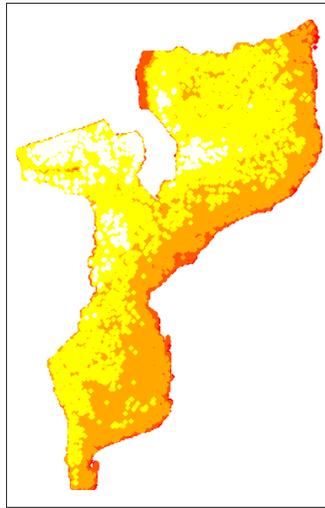
	1	2	3	4	5
	35.547	22.715	11.603	11.111	11.112

Factor 1 Scores - SON 10 YR AVG Climate



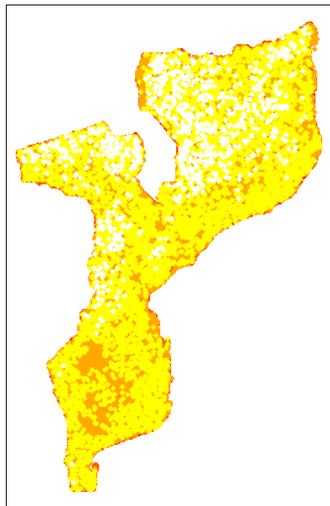
- [-2.744,-1.773]
- [-1.773,-0.8016]
- [-0.8016,0.1695]
- [0.1695,1.141]
- [1.141,2.112]

Factor 2 Scores - SON 10 YR AVG Climate



- [-3.536,-2.168]
- [-2.168,-0.7989]
- [-0.7989,0.5696]
- [0.5696,1.938]
- [1.938,3.307]

Factor 3 Scores - SON 10 YR AVG Climate



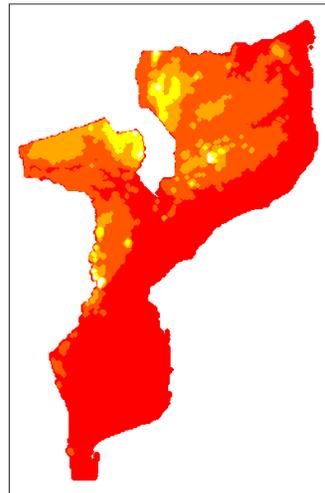
- [-2.127,-1.17]
- [-1.17,-0.2132]
- [-0.2132,0.7439]
- [0.7439,1.701]
- [1.701,2.656]

Factor 4 Scores - SON 10 YR AVG Climate



- [-6.884,-5.275]
- [-5.275,-3.665]
- [-3.665,-2.055]
- [-2.055,-0.4457]
- [-0.4457,1.164]

Factor 5 Scores - SON 10 YR AVG Climate



- [-1.193,0.1026]
- [0.1026,1.398]
- [1.398,2.693]
- [2.693,3.988]
- [3.988,5.284]

Conclusion: Use elev, loc&ppt, temp, q, p (125)

Appendix 11. 10 year average climate: K-means

10 year average climate – K means clustering

Distance metric is Euclidean distance

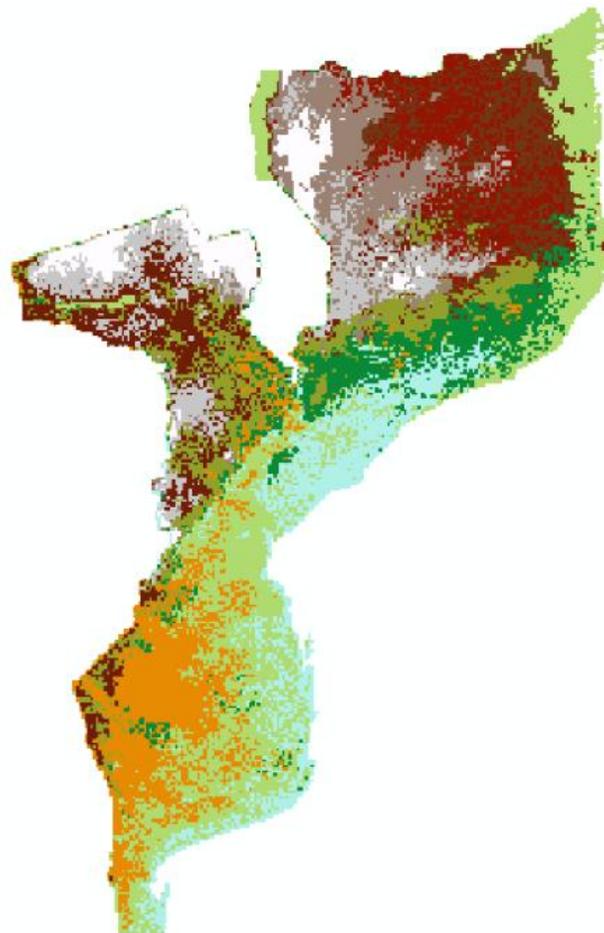
k-means splitting cases into 12 groups

Summary statistics for all cases

Variable	Between SS	df	Within SS	df	F-ratio
FACTOR(1)	24083.959	11	3525.0027598		17141.686
FACTOR(2)	23173.665	11	4435.2727598		13108.676
FACTOR(5)	23699.832	11	3909.2427598		15210.301
** TOTAL **	70957.456	33	11869.5282794		

Cluster 1 of 12 contains 2518 cases

Members		Statistics					
Case	Distance	Variable	Minimum	Mean	Maximum	St.Dev.	
Case 430	0.52	FACTOR(1)	-1.66	-0.62	0.37	0.39	
Case 6410	0.38	FACTOR(2)	-3.59	-1.54	-0.80	0.40	
Case 6522	0.28	FACTOR(5)	-0.54	0.94	1.69	0.32	



Appendix 12. 10 year average climate DJF: K-means

Distance metric is Euclidean distance

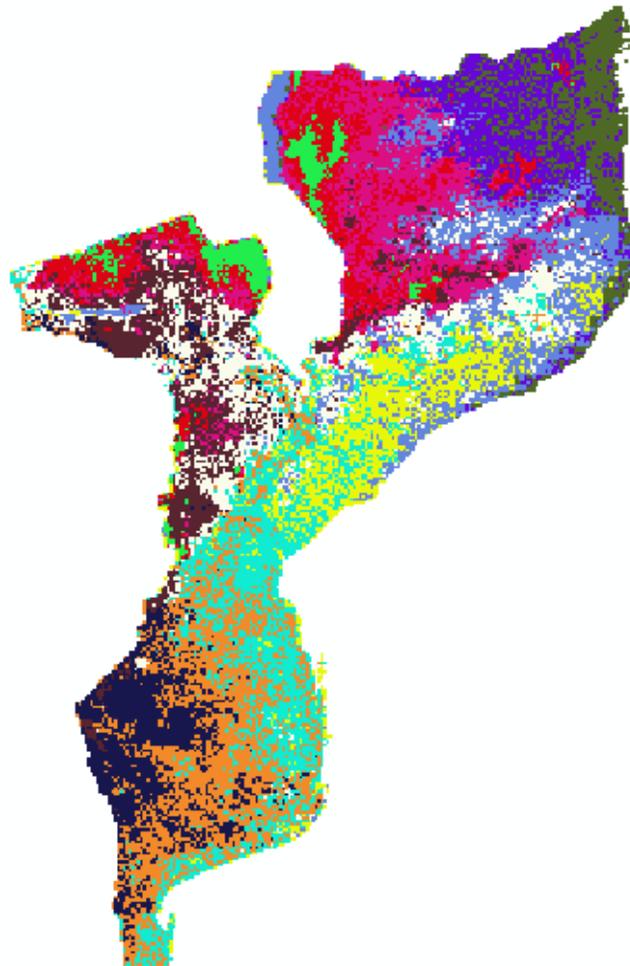
k-means splitting cases into 12 groups

Summary statistics for all cases

Variable	Between SS	df	Within SS	df	F-ratio
FACTOR(1)	23851.104	11	3757.9027598		15923.847
FACTOR(2)	23096.249	11	4512.7427598		12840.617
FACTOR(5)	23781.738	11	3826.9727598		15590.947
** TOTAL **	70729.090	33	12097.6282794		

Cluster 1 of 12 contains 3398 cases

Members		Statistics					
Case	Distance	Variable	Minimum	Mean	Maximum	St.Dev.	
Case 6995	0.43	FACTOR(1)	-1.97	-1.01	-0.01	0.40	
Case 7122	0.37	FACTOR(2)	-1.29	-0.35	0.46	0.34	
Case 7252	0.29	FACTOR(5)	-0.12	0.97	2.16	0.31	



Appendix 13. 10 year average climate MAM: K-means

Distance metric is Euclidean distance

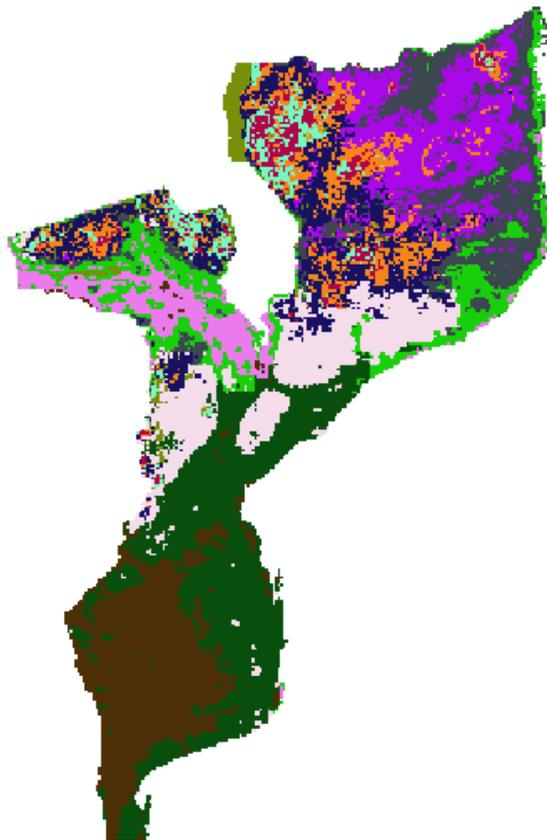
k-means splitting cases into 12 groups

Summary statistics for all cases

Variable	Between SS	df	Within SS	df	F-ratio
FACTOR(1)	25215.132	11	2393.9027598		26426.521
FACTOR(2)	25065.706	11	2543.6727598		24723.074
FACTOR(5)	25074.813	11	2534.0827598		24825.703
** TOTAL **	75355.651	33	7471.6682794		

Cluster 1 of 12 contains 3824 cases

Members		Statistics					
Case	Distance	Variable	Minimum	Mean	Maximum	St.Dev.	
Case 12161	0.81	FACTOR(1)	0.34	1.33	2.14	0.24	
Case 12533	1.13	FACTOR(2)	-3.41	-1.42	-0.56	0.36	
Case 12534	1.04	FACTOR(5)	0.92	1.52	3.50	0.36	



Appendix 14. 10 year average climate JJA: K-means

Distance metric is Euclidean distance

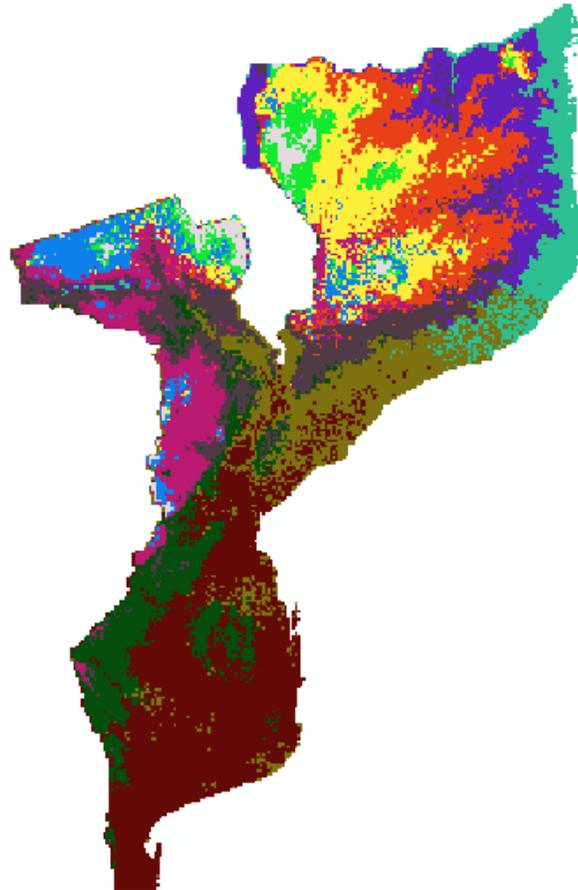
k-means splitting cases into 12 groups

Summary statistics for all cases

Variable	Between SS	df	Within SS	df	F-ratio
FACTOR(1)	24582.643	11	3026.1827598		20380.651
FACTOR(4)	25706.359	11	1902.5627598		33898.912
FACTOR(5)	25862.489	11	1746.3327598		37156.001
** TOTAL **	76151.492	33	6675.0882794		

Cluster 1 of 12 contains 5918 cases

Members		Statistics					
Case	Distance	Variable	Minimum	Mean	Maximum	St.Dev.	
Case 12982	0.24	FACTOR(1)	0.80	1.28	2.16	0.27	
Case 13446	0.26	FACTOR(4)	0.44	0.91	1.16	0.15	
Case 13754	0.21	FACTOR(5)	-1.22	-0.93	-0.26	0.15	



Appendix 15. 10 year average climate SON: K-means

Distance metric is Euclidean distance

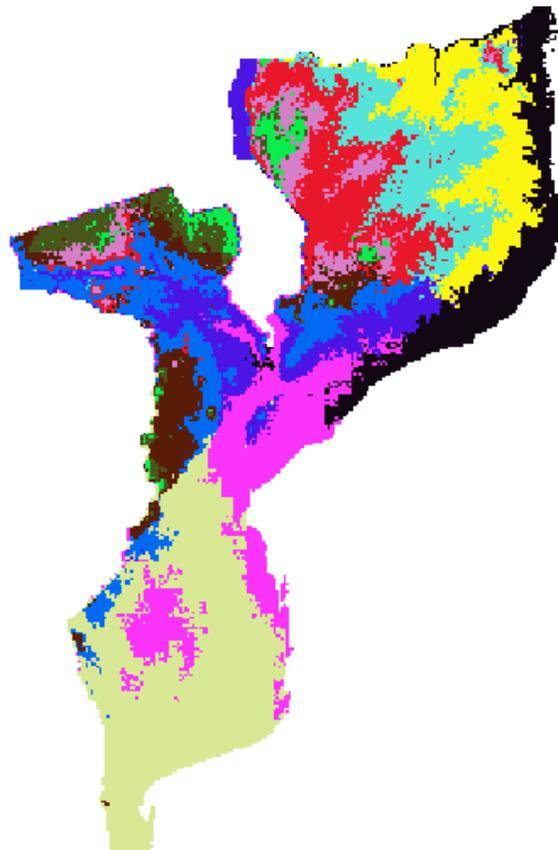
k-means splitting cases into 12 groups

Summary statistics for all cases

Variable	Between SS	df	Within SS	df	F-ratio
FACTOR(1)	24193.188	11	3415.7727598		17770.046
FACTOR(4)	25528.674	11	2080.1427598		30790.689
FACTOR(5)	25629.715	11	1979.3727598		32486.288
** TOTAL **	75351.576	33	7475.3082794		

Cluster 1 of 12 contains 6029 cases

Members		Statistics					
Case	Distance	Variable	Minimum	Mean	Maximum	St.Dev.	
Case 6637	0.31	FACTOR(1)	-2.74	-1.23	-0.64	0.37	
Case 8695	0.49	FACTOR(4)	-0.14	0.78	1.16	0.24	
Case 8874	0.29	FACTOR(5)	-1.19	-0.78	0.49	0.26	



Appendix 16. Soil: PCA

Latent Roots (Eigenvalues)

1	2	3	4	5
5.248	2.982	1.713	1.110	0.941
6	7	8	9	10
0.627	0.558	0.315	0.257	0.132
11	12	13	14	
0.079	0.029	0.006	0.003	

Component loadings

	1	2	3
TC_ECE_R	0.453	0.446	-0.722
TC_ESP_R	0.433	0.404	-0.708
TC_REF_BULK_	-0.348	0.779	0.389
TC_SILTC_R	0.675	-0.320	0.373
TC_PH_H2O_R	0.438	0.744	0.356
TC_BS_R	0.283	0.743	0.347
TC_OC_R	0.687	-0.117	0.229
MEANELEV5KM	-0.243	-0.395	0.197
TC_GRAVEL_R	-0.019	-0.121	0.193
TC_CLAY_R	0.826	-0.264	0.115
TC_SAND_R	-0.712	0.667	0.068
TC_CEC_SOIL_	0.968	-0.004	0.057
TC_CEC_CLAY_	0.649	0.323	0.038
TC_TEB_R	0.964	0.045	0.033

Variance Explained by Components

1	2	3
5.248	2.982	1.713

Percent of Total Variance Explained

1	2	3
37.487	21.299	12.235

Rotated Loading Matrix (VARIMAX, Gamma = 1.0000)

	1	2	3
TC_CEC_SOIL_	0.921	0.153	0.259
TC_TEB_R	0.900	0.182	0.300
TC_CLAY_R	0.872	-0.056	0.047
TC_SAND_R	-0.836	0.507	0.021
TC_SILTC_R	0.799	0.010	-0.241
TC_OC_R	0.724	0.109	-0.025
TC_CEC_CLAY_	0.529	0.379	0.322
TC_PH_H2O_R	0.282	0.871	0.183
TC_BS_R	0.136	0.845	0.140
TC_REF_BULK_	-0.458	0.815	-0.079
TC_ECE_R	0.152	0.065	0.948
TC_ESP_R	0.149	0.034	0.910
MEANELEV5KM	-0.079	-0.264	-0.421
TC_GRAVEL_R	0.056	-0.006	-0.222

COMPONENTS:

Soil composition	Soil moisture	Soil conductivity/mobility
------------------	---------------	----------------------------

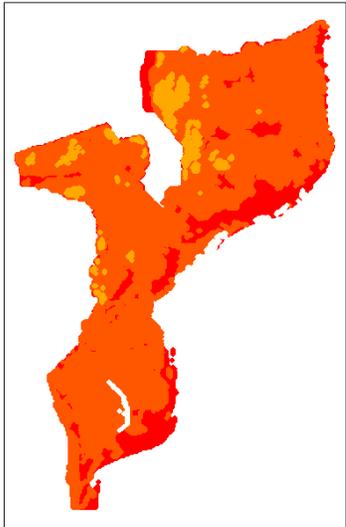
"Variance" Explained by Rotated Components

1	2	3
4.924	2.684	2.335

Percent of Total Variance Explained

1	2	3
35.171	19.174	16.676

Factor 1 Scores - Soil



- [-2.715,-0.6802]
- [-0.6802,1.355]
- [1.355,3.39]
- [3.39,5.425]
- [5.425,7.46]

Factor 2 Scores - Soil



- [-2.793,1.646]
- [1.646,6.086]
- [6.086,10.53]
- [10.53,14.96]
- [14.96,19.4]

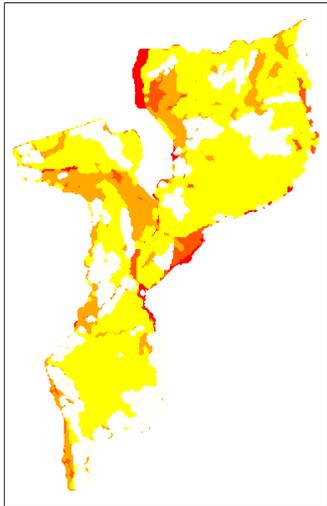
Soil Composition

TC_CEC_SOIL_
 TC_TEB_R
 TC_CLAY_R
 TC_SAND_R
 TC_SILTC_R
 TC_OC_R
 TC_CEC_CLAY_

Soil Moisture

TC_PH_H2O_R
 TC_BS_R
 TC_REF_BULK_

Factor 3 Scores - Soil



- [-3.488,-2.42]
- [-2.42,-1.352]
- [-1.352,-0.2833]
- [-0.2833,0.785]
- [0.785,1.853]

Conductivity/Mobility/Movement

TC_ECE_R
 TC_ESP_R

Appendix 17. Climate & Soil: PCA

Climate+Soil – Identified 5 components

Latent Roots (Eigenvalues)

	1	2	3	4	5
	5.320	4.088	2.321	1.869	1.634
	6	7	8	9	10
	1.005	0.995	0.711	0.589	0.380
	11	12	13	14	15
	0.305	0.238	0.197	0.142	0.122
	16	17	18	19	20
	0.047	0.026	0.007	0.003	0.001

Component loadings

	1	2	3	4	5
X	-0.195	0.165	0.430	-0.789	-0.046
TC_ESP_R	0.494	-0.113	0.132	0.045	-0.820
TC_ECE_R	0.553	-0.195	0.065	0.105	-0.785
LAVG10	0.430	-0.455	-0.056	0.270	0.314
TC_SILTC_R	0.485	0.577	0.061	0.078	0.308
TC_OC_R	0.577	0.411	0.124	0.052	0.182
TC_REF_BULK_	-0.194	-0.603	0.662	0.163	0.151
TC_BS_R	0.381	-0.322	0.721	0.046	0.149
MEANELEV5KM	-0.589	0.599	0.208	0.470	-0.125
MEANMAXCRV5K	-0.588	0.601	0.205	0.471	-0.124
TC_PH_H2O_R	0.501	-0.255	0.718	0.192	0.116
PAVG10	-0.383	0.391	0.424	-0.543	-0.113
MEANLONGCONV	0.562	-0.546	-0.312	-0.486	0.086
TC_CLAY_R	0.636	0.633	0.123	0.001	0.046
TC_CEC_SOIL_	0.868	0.394	0.109	0.014	0.044
TC_SAND_R	-0.499	-0.759	0.351	0.083	-0.037
Y	-0.459	0.580	0.296	-0.322	-0.034
TC_TEB_R	0.879	0.357	0.136	0.001	0.018
P	0.007	0.005	0.003	-0.018	-0.004
Q	-0.013	0.007	0.019	-0.005	-0.002

Variance Explained by Components

	1	2	3	4	5
	5.320	4.088	2.321	1.869	1.634

Percent of Total Variance Explained

	1	2	3	4	5
	26.602	20.438	11.606	9.345	8.170

Rotated Loading Matrix (VARIMAX, Gamma = 1.0000)

	1	2	3	4	5
TC_CEC_SOIL_	0.904	0.185	0.119	0.061	-0.234
TC_CLAY_R	0.891	-0.056	-0.015	-0.093	-0.125
TC_TEB_R	0.884	0.206	0.150	0.050	-0.268
TC_SAND_R	-0.833	0.006	0.510	0.031	0.021
TC_SILT_R	0.799	-0.083	-0.001	0.016	0.163
TC_OC_R	0.735	0.027	0.105	0.027	-0.008
MEANMAXCRV5K	-0.029	-0.975	-0.127	-0.092	0.099
MEANELEV5KM	-0.031	-0.975	-0.124	-0.095	0.099
MEANLONGCONV	0.029	0.966	-0.002	0.097	-0.108
TC_PH_H2O_R	0.283	0.084	0.870	0.070	-0.180
TC_BS_R	0.154	0.152	0.857	-0.049	-0.101
TC_REF_BULK_	-0.445	-0.033	0.828	0.015	0.069
X	-0.041	0.148	0.100	-0.915	0.071
PAVG10	-0.035	-0.222	-0.003	-0.854	0.079
Y	0.047	-0.442	-0.143	-0.696	0.193
LAVG10	0.088	0.369	0.343	0.547	0.072
TC_ESP_R	0.122	0.102	0.080	0.007	-0.957
TC_ECE_R	0.116	0.166	0.087	0.131	-0.954
P	0.007	0.010	-0.002	-0.016	-0.004
Q	-0.004	-0.014	0.010	-0.018	0.002

COMPONENTS:

	Soil Composition	Elevation	Soil Moisture	Climate & Location	Soil Conductivity
--	---------------------	-----------	------------------	-----------------------	----------------------

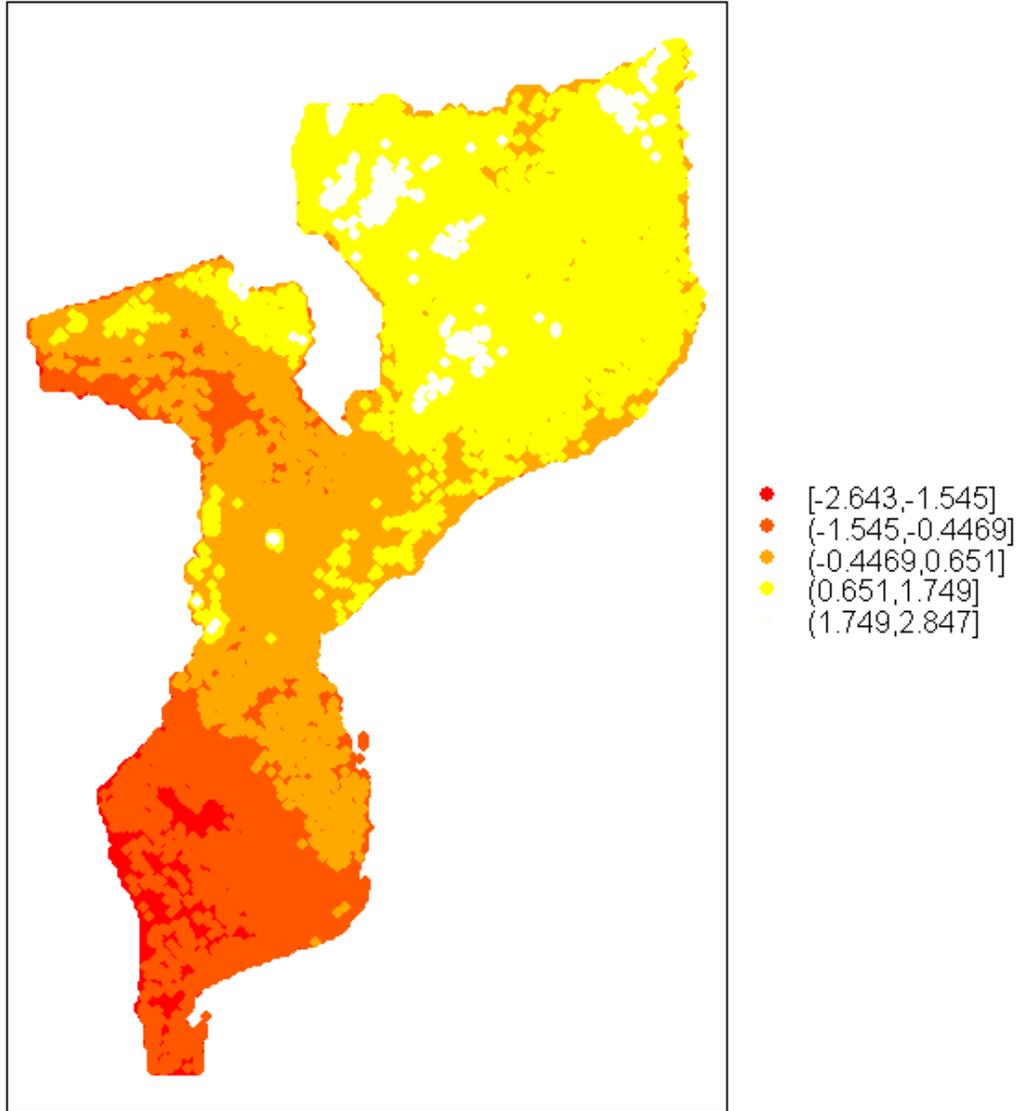
"Variance" Explained by Rotated Components

	1	2	3	4	5
	4.612	3.395	2.678	2.420	2.128

Percent of Total Variance Explained

	1	2	3	4	5
	23.058	16.976	13.389	12.100	10.638

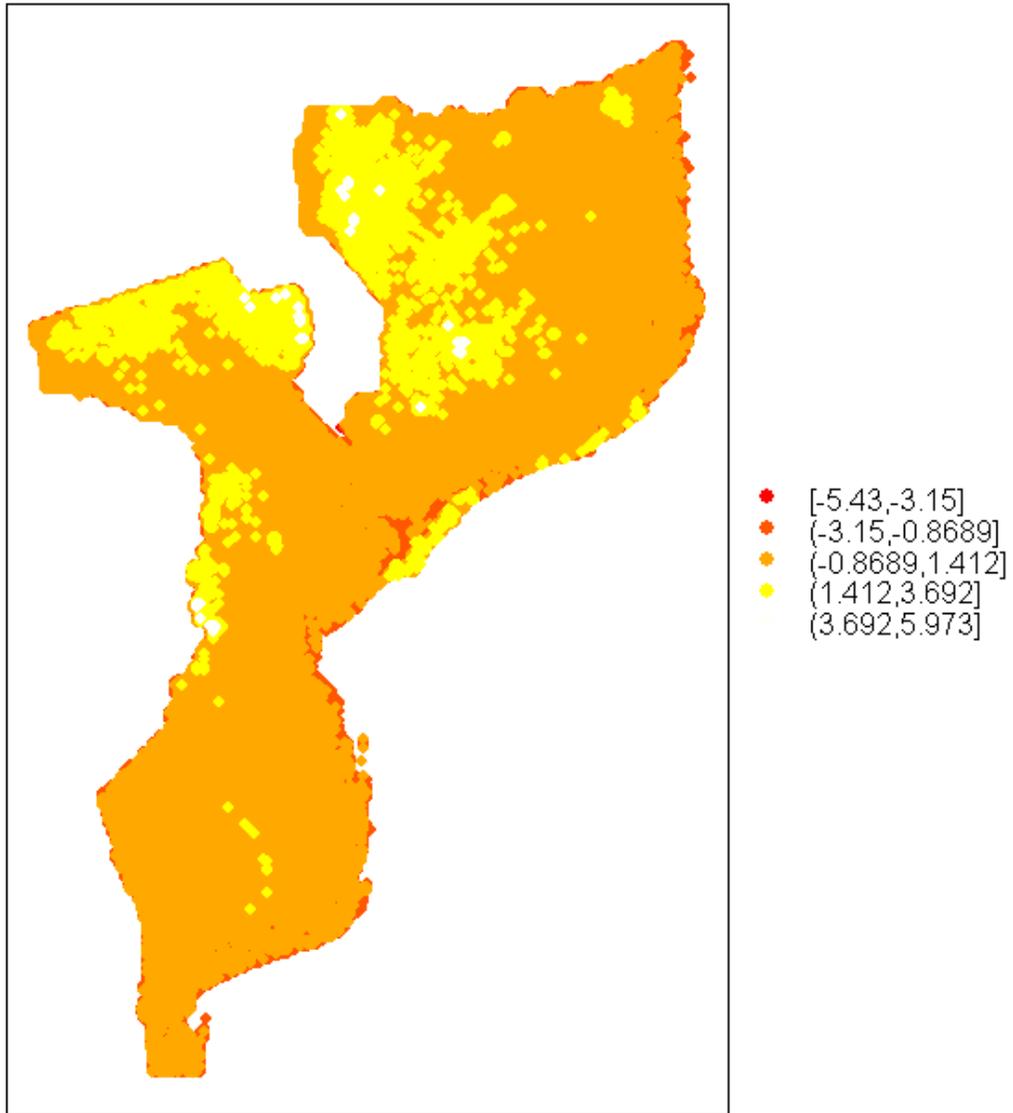
Factor 1 Scores - 10 YR AVG AgroClimate



Soil Composition

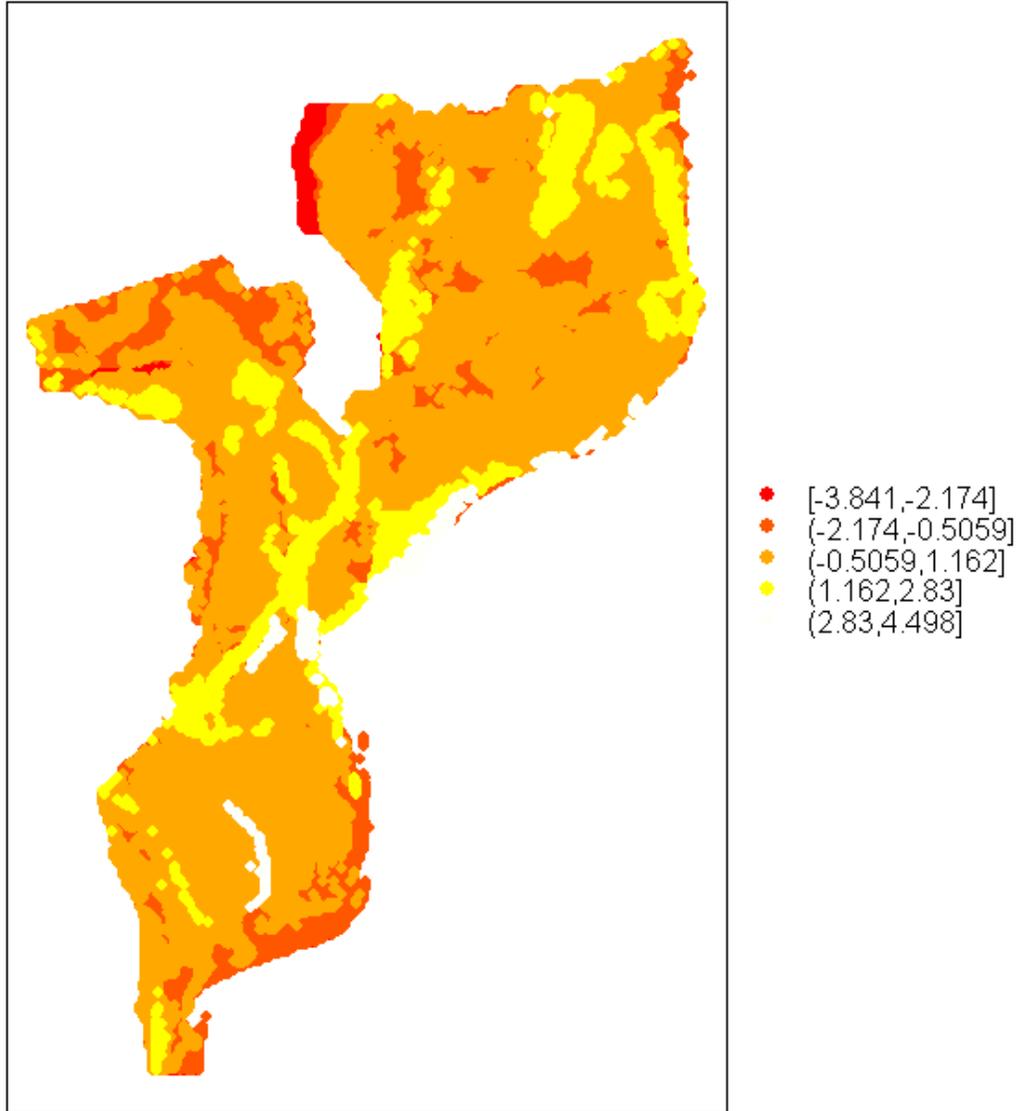
TC_CEC_SOIL_	0.904
TC_CLAY_R	0.891
TC_TEB_R	0.884
TC_SAND_R	-0.833
TC_SILTC_R	0.799
TC_OC_R	0.735

Factor 2 Scores - 10 YR AVG AgroClimate



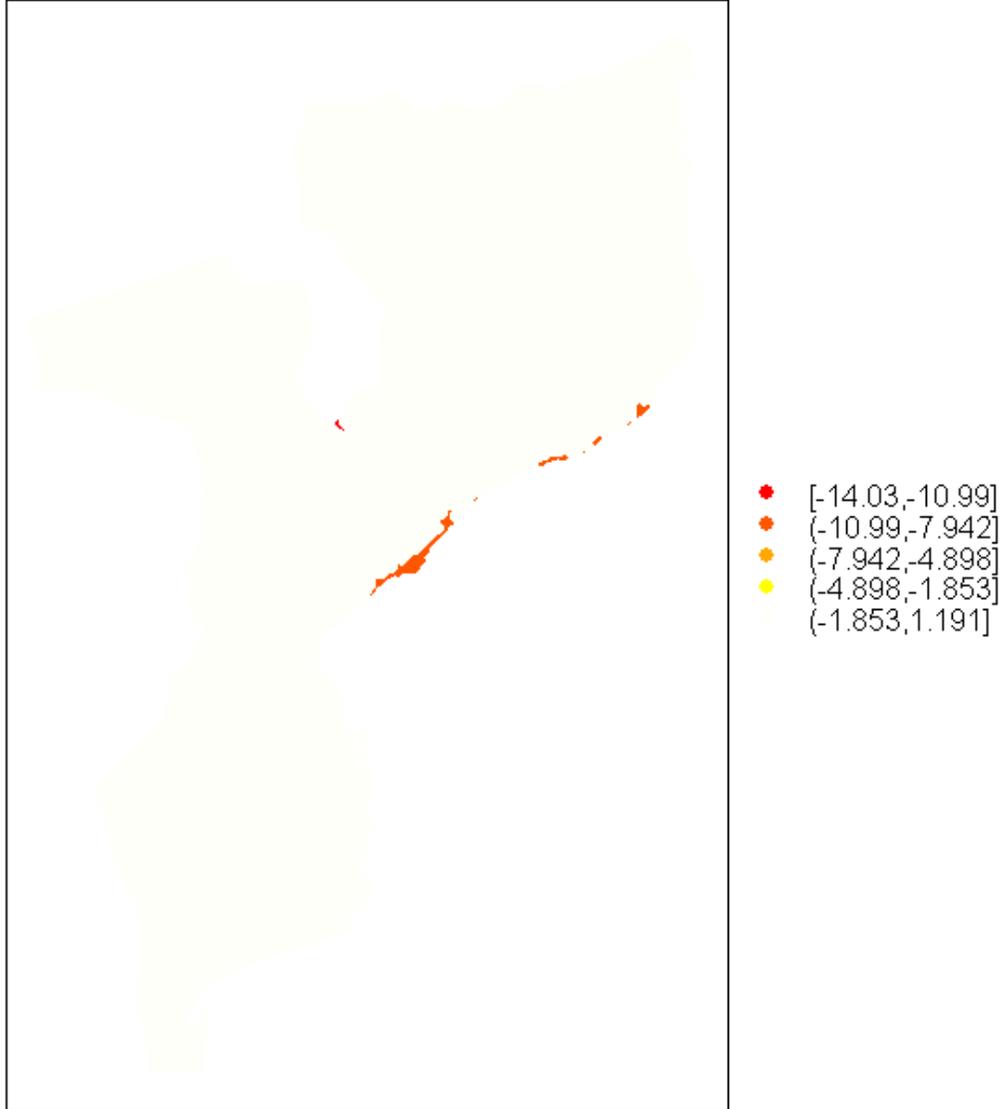
MEANMAXCRV5K	-0.975
MEANELEV5KM	-0.975
MEANLONGCONV	0.966

Factor 3 Scores - 10 YR AVG AgroClimate



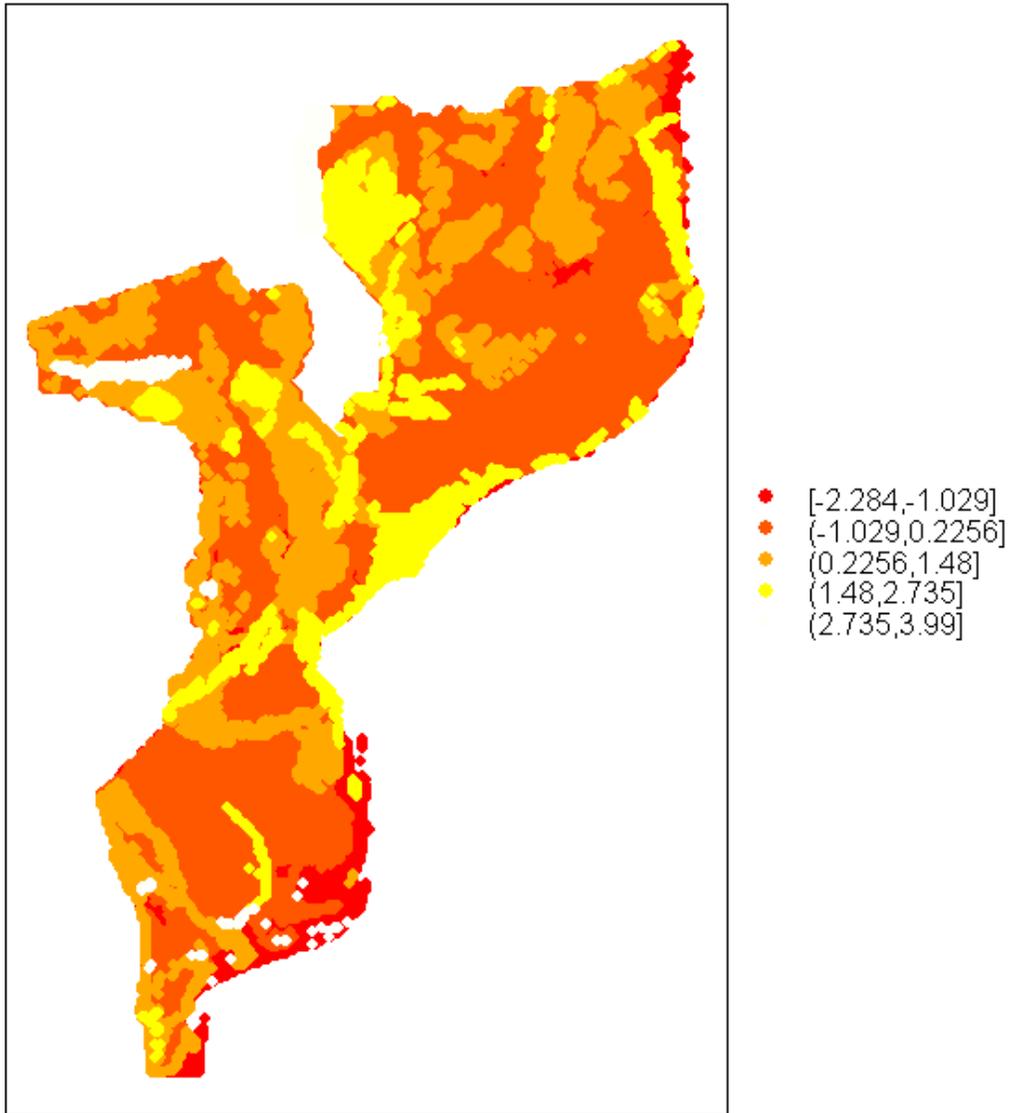
TC_PH_H2O_R	0.87
TC_BS_R	0.857
TC_REF_BULK_	0.828

Factor 4 Scores - 10 YR AVG AgroClimate



X	-0.915
PAVG10	-0.854
Y	-0.696
LAVG10	0.547

Factor 5 Scores - 10 YR AVG AgroClimate



TC_ESP_R	-0.957
TC_ECE_R	-0.954

Appendix 18. Climate & Soil: K-means

10 year average climate + Soil – K means clustering

Distance metric is Euclidean distance

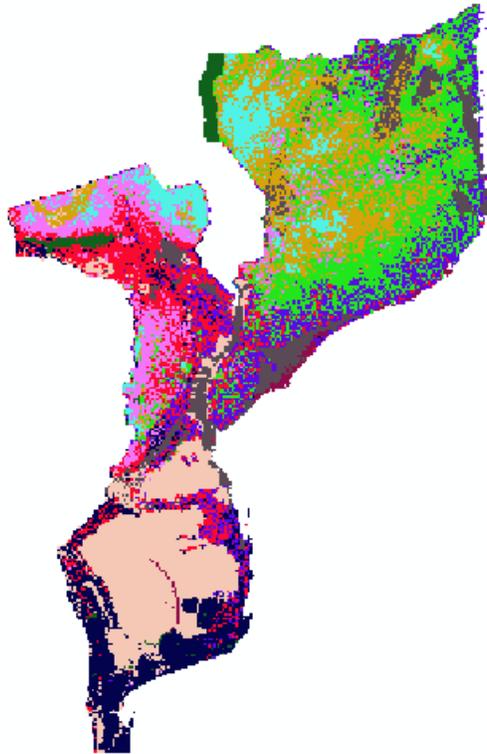
k-means splitting cases into 12 groups

Summary statistics for all cases

Variable	Between SS	df	Within SS	df	F-ratio
FACTOR(1)	20851.374	11	6330.6527171		8135.772
FACTOR(2)	21701.441	11	5480.4627171		9781.014
FACTOR(3)	21675.239	11	5506.6827171		9722.696
FACTOR(4)	24904.622	11	2277.4027171		27011.733
** TOTAL **	89132.675	44	19595.2108684		

Cluster 1 of 12 contains 4143 cases

Members			Statistics			
Case	Distance	Variable	Minimum	Mean	Maximum	St.Dev.
Case 7156	0.41	FACTOR(1)	-2.35	-1.14	0.52	0.57
Case 7288	0.83	FACTOR(2)	-1.98	-0.37	1.66	0.48
Case 7432	0.65	FACTOR(3)	-0.52	0.69	2.28	0.27
Case 7433	0.85	FACTOR(4)	-1.60	-0.68	0.72	0.31



Distance metric is Euclidean distance

k-means splitting cases into 12 groups

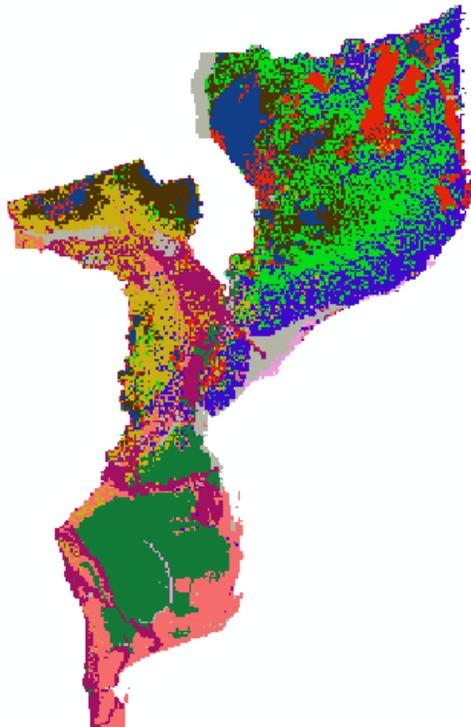
Summary statistics for all cases

Variable	Between SS	df	Within SS	df	F-ratio
FACTOR(1)	20429.468	11	6752.6427171		7473.017
FACTOR(2)	19856.790	11	7325.1627171		6695.834
FACTOR(4)	25408.349	11	1773.7027171		35384.184
FACTOR(5)	22190.560	11	4991.3527171		10981.522

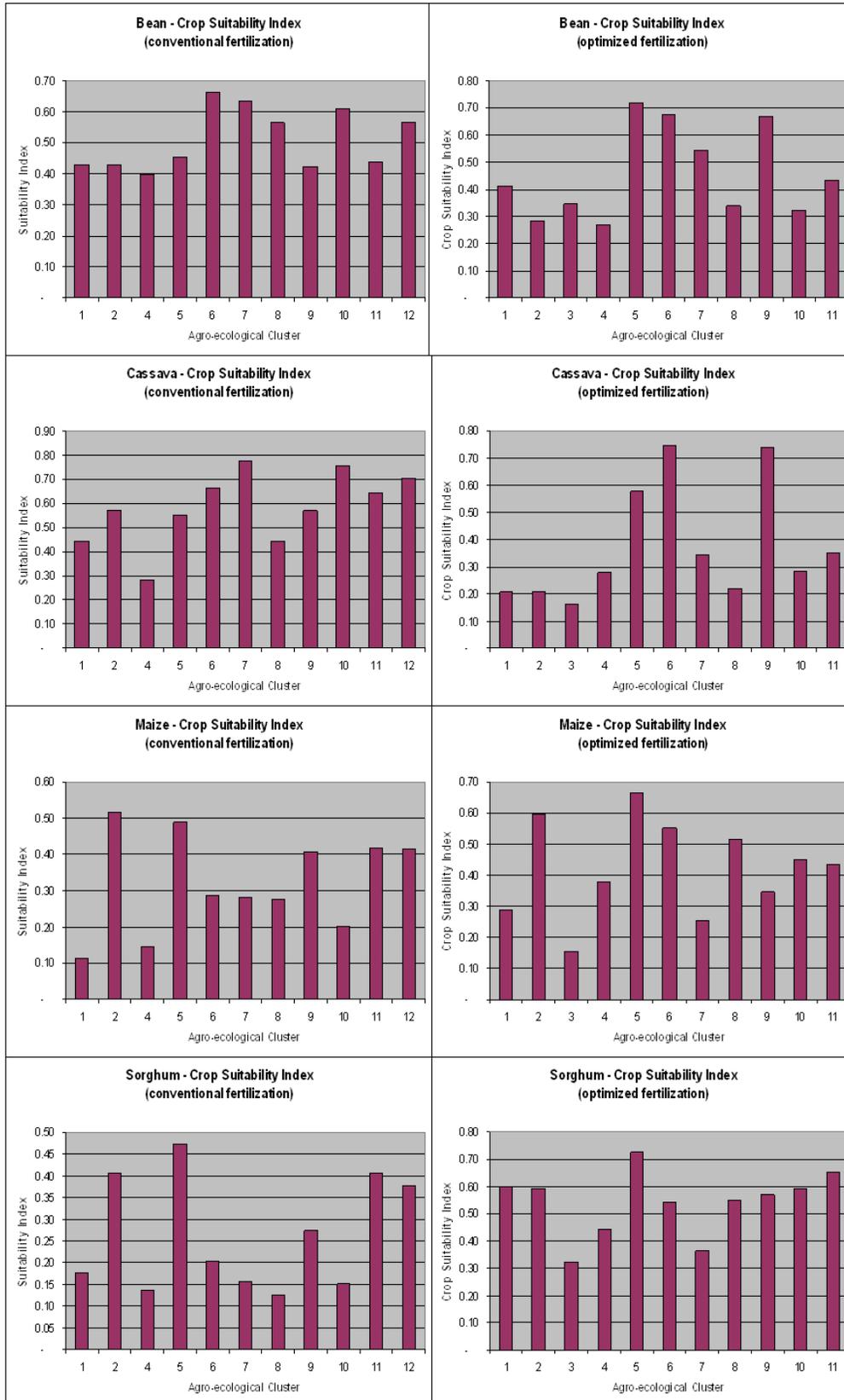
** TOTAL ** 87885.167 44 20842.8108684

Cluster 1 of 12 contains 3557 cases

Members			Statistics				
Case	Distance	Variable	Minimum	Mean	Maximum	St.Dev.	
Case 6211	0.46	FACTOR(1)	-2.35	-1.16	0.25	0.56	
Case 6319	0.50	FACTOR(2)	-1.89	-0.39	1.05	0.44	
Case 6898	0.40	FACTOR(4)	-1.60	-0.78	0.42	0.10	
Case 7155	0.35	FACTOR(5)	-0.64	-0.26	1.59	0.14	



Appendix 19. Top area crop CSI by fertilization and cluster



Appendix 20. CSI and CVI for major crops

