Monitoring the resilience of smallholder farmers to climate extremes in Sub-Saharan Africa

Recent evidence has emphasized the vulnerability of poor and near-poor rural households to climate shocks[1] with potential to undo gains in poverty alleviation[2]. In response resilience has become ubiquitous in international development programming. This turn to resilience has led to challenges in firstly theorizing resilience for development and, secondly, in measurement of the impact of climate shocks on livelihoods and of climate resilience. Recent publications have tackled the first of these challenges[3,4] and in this context resilience has been defined as a capacity to avoid poverty while buffering, preparing for, and recovering from a multitude of shocks and stresses[5-7]. This work emphasizes that resilience is a capacity possessed by an economic unit, and this capacity is composed of the ability to absorb a shock, recover quickly after a shock, and adapt to longer-run changes in the risk landscape[6].

To fully measure the impact of a climate shock on rural households and to identify the resilience of households requires high temporal frequency observations of livelihoods that coincide with the occurrence of climate shocks. For much of the developing world available data does not permit high temporal frequency (e.g. annual to sub-annual) observations of livelihoods. Traditional socio-economic datasets covering poor rural populations include nationally representative household surveys (e.g. Demographic and Health Surveys (DHS), Living Standards Measurement Survey (LSMS)). These surveys capture detail on the socio-economic characteristics of farmers but do not capture local detail across wide spatial extents and due to their infrequent nature do not capture intra-household temporal variability in livelihoods. This data is not suitable for measuring climate shocks on rural households which in an ideal world would include measures of the same household pre-shock, during the shock, and post-shock.

Rural households, who are vulnerable to climate shocks, often rely on agricultural based livelihoods[8,9]. Further, the extensive spread of smallholder farmers across the landscape means that large groups fall within the gaps of monitoring tools such as household surveys and we often lack multi-temporal observations of their livelihoods pre- and post-climate shock exposure. Except in a few cases most household survey data covering smallholder farmers is either a two-time period panel dataset or cross-sectional, both of which are suboptimal for monitoring climate-resilience dynamics. However, given the subsistence and agricultural based livelihood strategies of many smallholders their livelihoods are to some extent tied to the performance of their fields and the underlying ecosystem. Thus, if predictive relationships between local cropland performance and livelihoods can be established then there is potential to proxy livelihoods across space and time by monitoring croplands and other spatial features that might be correlated with livelihoods (e.g. road networks or proximity to market towns). Beyond establishing cropland-livelihood linkages measuring the impact of climate shocks on rural households requires synoptic, local, and multi-temporal livelihood monitoring. These are characteristics are inherent to remote sensing observations of the land surface that capture agriculturally relevant information including land cover[10,11], cropping intensity[12], and crop yield[13]. While studies have linked remote sensing observations to measures of human wellbeing[14] including poverty[15,16] to our knowledge no studies have used remote sensing crop yield estimates to predict livelihood status, monitor how climate shocks impact livelihoods, and conduct resilience assessments.

Our research is exploring how the creation of pseudo-panel datasets of rural livelihoods, that predict livelihood dynamics over time, can improve our measurement of climate impacts. We are utilizing four waves of nationally representative waves of rural household survey data from Mozambique spanning the period 2002 to 2012. We are using two approaches to generate these pseudo-panel datasets. The first relies solely on cross-sectional household survey data that captures information at the same locations in multiple years but not from the same households. This information is then aggregated to higher spatial unit (e.g. the District or some other spatial cluster) to create a cluster based panel. The second approach relies on predicting livelihood status across space and time using remote sensing observations of croplands (Fig. 1a) and other spatial datasets (e.g. proximity to roads (Fig. 1b), population density, distance to towns). Each of these pseudo-panel datasets includes multiple livelihood indicators that include agricultural outcomes (e.g. crop yield), economic outcomes (e.g. farm income, total income), and measures of capabilities (asset levels, food security, health status). We have been working to generate these datasets with agricultural economists based at the Michigan State University office in Maputo, Mozambique.

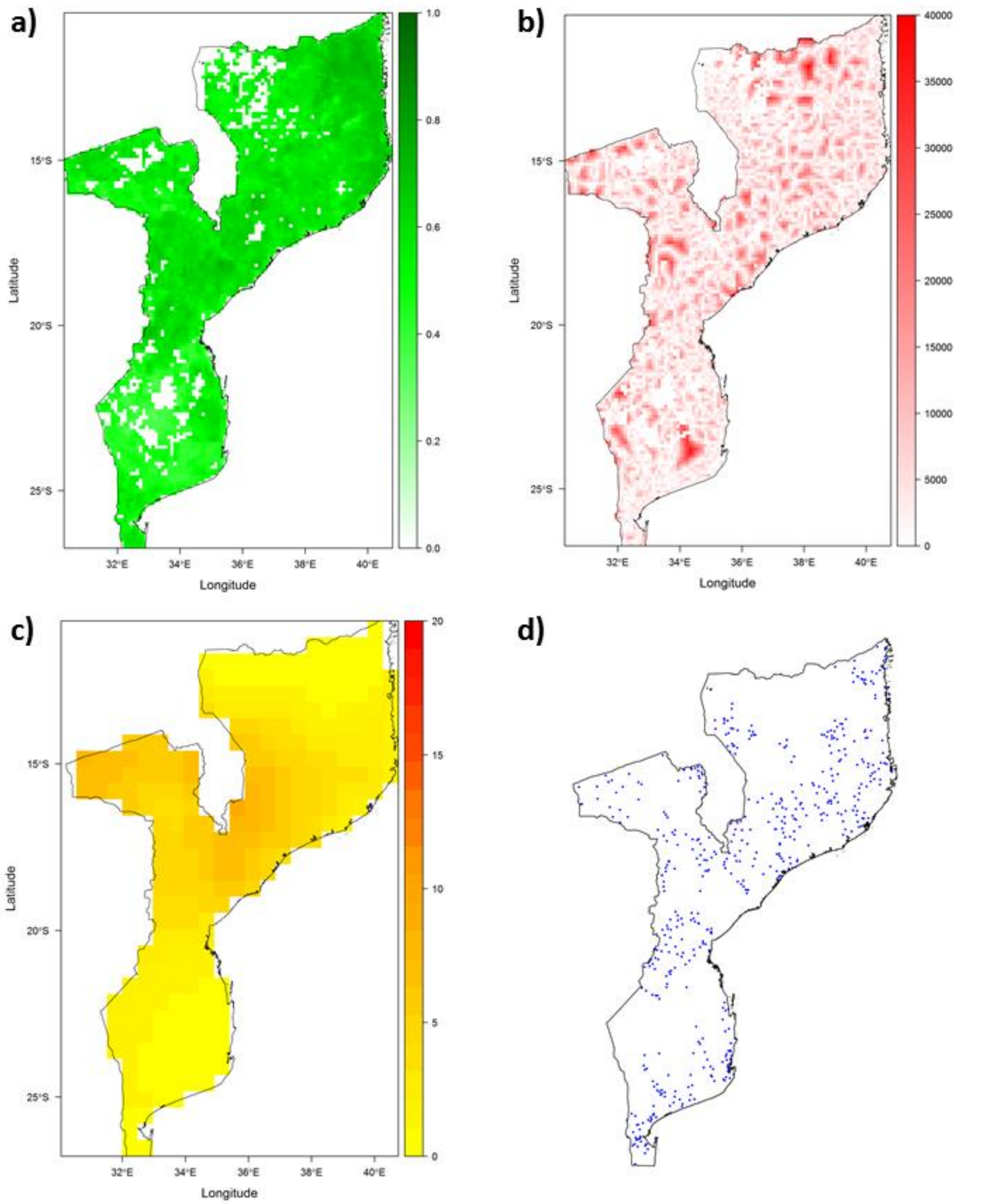

Figure 1 | a) Enhanced Vegetation Index (a measure vegetative greenness and proxy for biomass) over croplands and natural vegetation land covers in 2002 in Mozambique (derived from the MODIS MOD09A1 product), b) proximity to roads in Mozambique in meters, c) drought index scores across Mozambique computed from the

CRU dataset, and d) location of villages where households were surveyed for the 2002 and 2005 panel dataset as part of the Trabalho de Inquérito Agrícola (TIA) household survey.

We are fusing these two pseudo-panels with temperature and precipitation data to monitor the impact of precipitation shocks and extreme heat shocks on rural livelihoods (Fig. 1c). We are seeking to identify which of these two approaches to generating pseudo-panels of rural livelihoods better captures the impact of climate shocks. Second, we are seeking to identify how climate shocks impact different measures of livelihood outcomes and how well the different approaches to generating pseudo-panels accurately predict the dynamics of different livelihood outcomes. This is important as it has been shown that climate shocks can have different effects on different aspects of livelihoods and one single measure of a livelihood (e.g. crop yield) is not always a good indicator of total livelihood status. Finally, we are identifying how well these two different pseudo-panels capture the immediate impact of the shock on livelihoods and the persistence of the shock on livelihood performance (in other words the recovery capacity of the household). In order to validate our findings we are using a panel dataset of ~4000 households collected in 2002 and 2005 (Fig. 1d); if the pseudo-panels accurately capture the effect of climate shocks on livelihoods both the validation panel dataset and the pseudo-panels will report similar livelihood dynamics. This work is foundational to a workshop we are hosting at the National Socio-Environmental Synthesis Center (SESYNC) on this topic in January 2017.

Undertaking such analysis is pertinent for Mozambique due its high population share engaged in smallholder agriculture and vulnerability to climate shocks[17,18]; these characteristics are broadly reflective of much of Sub-Saharan Africa. We are hoping to identify the full impact (both immediate and short-run) of climate shocks on livelihoods, identify which livelihood indicators we can accurately monitor, and undertake such monitoring over a larger spatial extent in order to identify pockets of low-resilience. This dataset will be useful in targeting resources efficiently to regions with numerous low-resilient populations and providing the building blocks for rigorously testing what characteristics generate resilience.

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