Introduction

The weight of a baby at birth has important impacts for his future development. Education rates are lower among children who are born with a low birth weight and if a mother was born with a low birth weight then she is more likely to produce low birth weight children (especially girls). Low birth weight babies are therefore less likely to grow into healthy and economically productive members of society. Consequently these negative outcomes have dire implications for the health and wellbeing of future generations. Theoretical models link low birth weight to a variety of factors including maternal health care during pregnancy, socioeconomic status, maternal nutrition and environmental factors (including temperature, soil type, rainfall, and others) (eg. Mosley and Chen 1984, de Sherbinin 2011 for discussion in relation to child malnutrition). However, in empirical research the relationship between environmental characteristics and low birth weight are limitedly examined – likely because of data limitations. In this study we seek to expand the literature on the relationship between the biological environment, namely those environmental factors related to climate change, and low birth weight. The results of the analysis can then be used to help quantify the human health impacts of changing climate patterns as well as facilitate targeted policy efforts to improve health. Using spatially referenced Demographic and Health Survey (DHS) data and detailed environmental information, we can link individual pregnancies to the locally relevant environmental characteristics.

The weight of an infant at birth is the result of a variety of biological factors and growth *in utero* (Mwabu 2008 also see Kramer 1987 for an extensive discussion). To explain the variation in birth weight due to biology, researchers generally rely on parental growth measures. *In utero* growth reflects many of the mother's habits during pregnancy, including (but not limited to) caloric intake and weight gain (Kramer 1987). In developing countries where many poor people rely on locally produced food for the majority of their caloric intake, shifts in climate and weather patterns can dramatically reduce agricultural productivity, reducing overall food availability (Funk and Brown 2009). Kenya represents one such developing country and because much of Kenya faces increasing risk of drought, including many poor and marginalized farmers and pastoralists, increasing droughts will result in dramatic decreases to crop production and food availability (Funk et al., 2010; Williams and Funk 2010). The goal of this study is to determine the relationship between changes in environmental variables related to crop production (specifically rainfall and the Normalized Difference Vegetation Index (NDVI) – a measure of vegetation growth) and birth weight after adjusting for vulnerability to climate patterns, local food prices, and socioeconomic characteristics.

Each pregnancy resulting in a live birth (and where birth weight was measured) will be linked to the corresponding monthly measures of crop growth (as represented by NVDI) and rainfall as well as the standard biological and socioeconomic control variables. In this way we can determine if reduced food availability, as measured through these environmental factors, is linked to low birth weights.

Data

There are three primary types of data used for this analysis – health, environmental/geographical and economic. The health information comes from the two most recent Demographic and Health Survey (DHS) datasets, 2008/09 and 1998[1]. These spatially referenced data contain detailed information about maternal characteristics and provide information about the health of infants including their birth weights. The most recently born child within the household will be used as the dependent variable. We pull the datasets to produce a sufficiently large and representative sample of births (approximately 10,000 births from the two surveys). Mother's education, mother's height, gestational age of child (the DHS retrospective calendar will be used to calculate the gestational age of the child in months), sex of the child, time since previous birth, mother's age at birth, and birth month and year (to account for any seasonality and external time factors unrelated to this analysis) will be included as control variables.

We use several types of environmental data – NDVI, livelihood zone and rainfall. Normalized Difference Vegetation Index (NDVI) comes from remote sensors which are commonly used to measure and map changes in geophysical features of the earth. Essentially, NDVI provides an indication of the amount of vegetation present in an area and livelihood zone data. NDVI represents the amount of "greenness" and reflects rainfall and temperature trends in a specific location. It has been used to predict cropped area and agricultural production (Rojas 2011). Ten day average NDVI is readily available from FEWS NET (see fews.net). Figure 1 presents NDVI for Kenya and reveals the large amount of variation in greenness across the country. NDVI ranges in value from -1 to 1. An area with limited vegetation has a score of about -.1 while a very green area is described by a score of about .6.

The livelihood zone data (Figure 2) come from the US Agency for International Development's Famine Early Warning Systems Network's (FEWS NET) recent efforts to characterize the dominant livelihood strategies in a number of developing countries. With the use of local weather patterns, market information and expert knowledge, FEWS NET has constructed zones that characterize the dominant strategy used to produce money and food in a general area. We incorporate the livelihood data into the analysis based on our assumption that individuals living within certain livelihood zones have a differential reliance on the environment. Specifically, we anticipate that individuals living in the more marginalized farming areas and the pastoral areas in the east may be more susceptible to climatic shifts. Individuals living in the Western area of Kenya, on the other hand, are rarely faced with inconsistent or decreasing rainfall and rely on fairly consistent crop production to meet their caloric needs. Due to the significant variation of rainfall in Kenya and

[1] DHS data was also collected in 2003 but because it was not geo-referenced it can not be properly merged with the environmental and economic data.

its impact on crop growth we also include rainfall data. Rainfall are interpolated from a combination of ground based meteorological stations, remotely sensed data, and *a priori* knowledge of climatic patterns within Kenya.

The final type of data used in this analysis is economic data. The Kenya price data is derived from 8 markets in Kenya: Mombasa, Nairobi, Eldoret, Kisumu, Kitui, Lodwar, Mandera and Marsabit. The data are from a continuously updated price database comprised of food prices from 232 markets in 39 countries, sourced from both the FAO and the US Agency for International Development's Famine Early Warning Systems Network (FEWS NET). There are 124 different commodities in the database, which were selected by local experts as appropriate to assess food security in the selected area. The database has retail price data in local currencies from 1997 to 2011, but the starting year of each series varies by market.

Merging data

DHS data is spatially referenced at the level of the sampling cluster. However, to preserve anonymity the cluster is shifted randomly within a radius of under 10 km (this radius varies according to survey year and if the cluster is urban or rural). We therefore attribute each cluster with the average and standard deviation of the NDVI value of the 10 km radius surrounding each cluster.

The location of the cluster will also be used to determine the nearest market. The cluster will then be attributed with the price values (mean and standard deviation) of the nearest market.

Methods

Given the hierarchical nature of the data we will use multilevel models (Gelman 2006; Gelman and Hill 2006) to examine birth weights. Individuals are nested within clusters to account for the potential sampling variation. We will use fixed effects for markets and for livelihood zones. Distance to market and NDVI will be incorporated as cluster-level independent variables.

Anticipated Results

The results of our analysis will highlight the relationship between birth weight and environmental factors reflecting changing climate patterns. We anticipate that even after controlling for food prices, socioeconomic variables and biological variables, women who were pregnant when less food was available will be more likely to have given birth to a baby with low birth weight. We also anticipate that this relationship will vary by livelihood and that women who reside in communities dependent on rainfed agriculture will be more sensitive to the impacts of reduced rainfall and lower NDVI. Our research will assist in developing targeted aid strategies to identify the most at risk segments of the population. These relationships are particularly important as Kenya continues to warm and dry.

Figure 1: Kenyan NDVI During the Growing Season of 2011

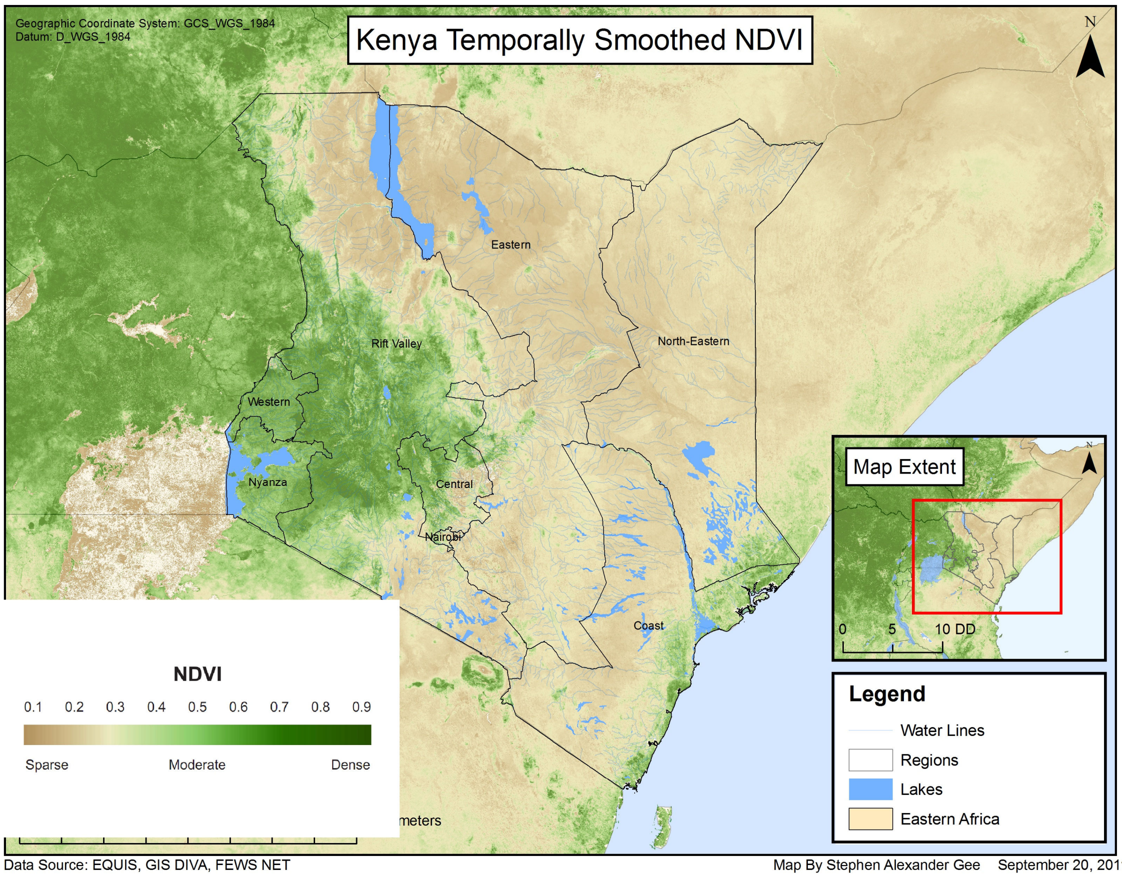
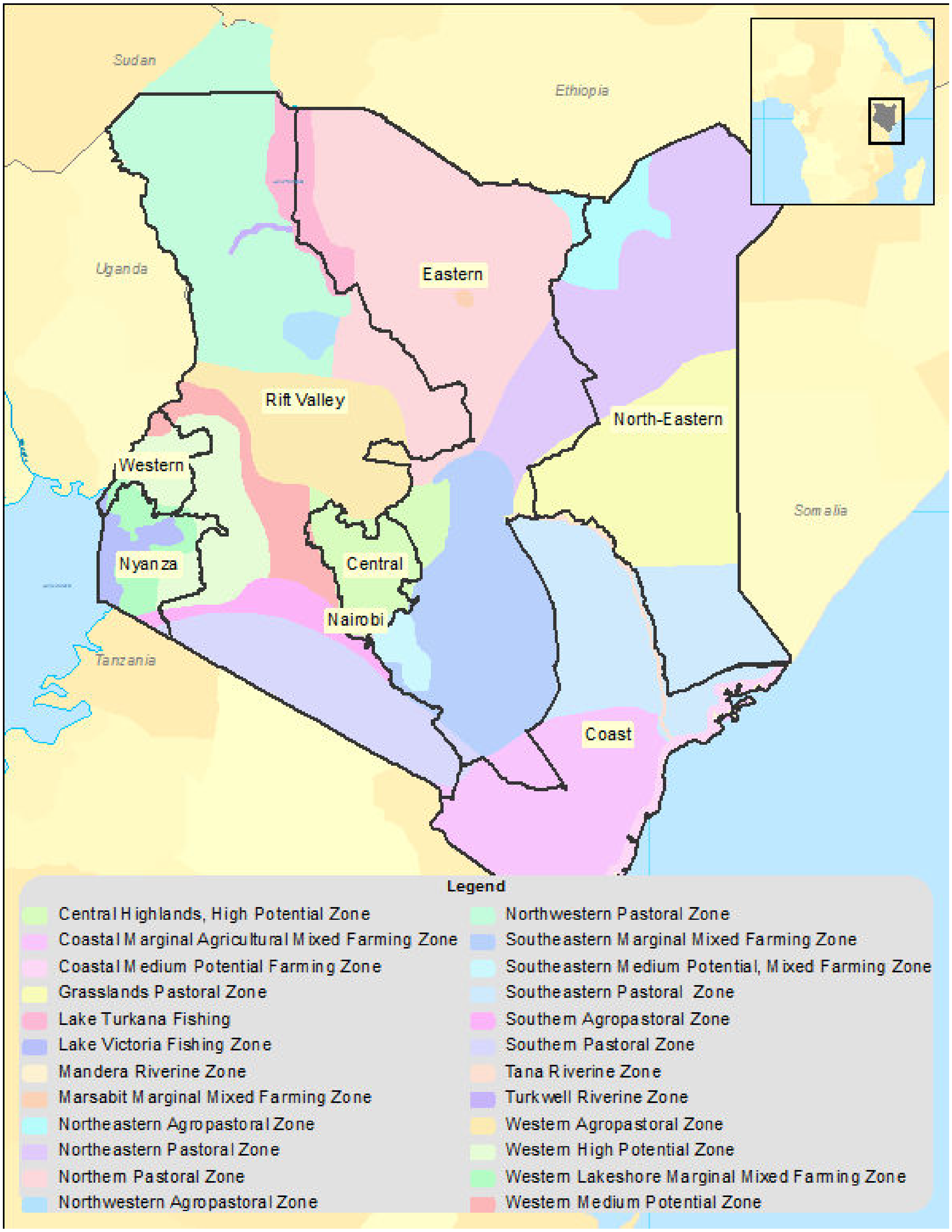


Figure 2: Kenyan Livelihood Zones and Regional Boundaries



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